INVESTIGATING THE TRANSPORTATION EFFICIENCY OF RIDE-HAILING SERVICES BY CONSIDERING EMPTY TRIPS:

THE CASE OF AUSTIN, TEXAS

by

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ABBREVIATIONS

AV	Autonomous Vehicle
CAMPO	Capital Area Metropolitan Planning Organization
CTA	Commercial Transport Apps
DfT	Department for Transport
GHG	Greenhouse Gas
GIS	Geographic Information System
GPS	Global Positioning System
ICT	Information and Communication Technologies
O-D	Origin Destination
PHT	Passenger Hours Travelled
PHV	Private Hire Vehicle
RMI	Rocky Mountain Institute
SFCTA	San Francisco Country Transportation Authority
TNC	Transportation Network Companies
TRB	Transport Research Board
UVHT	Unoccupied Vehicle Hours Travelled
UVMT	Unoccupied Vehicles Miles Travelled
VHT	Vehicle Hours Travelled
VMT	Vehicle Miles Travelled

EXECUTIVE SUMMARY

The popularity of app-based on-demand ride services, in other words, ride-hailing services has increased rapidly across the world in the last decade after the introduction of Uber in 2009. The taxi industry in major cities has experienced significant change due to this disruptive innovation in mobility. The growing popularity of ride-hailing services around the world is mainly a result of the technological innovations that give travellers many advantages. They provide a more reliable and accessible transport service with shorter waiting times to more locations and with a lower cost than traditional taxi services. However, in parallel with this rapid growth of ride-hailing services, many questions have arisen about their role in urban transport. Most prior studies have already revealed that ride-hailing services lead to changes in the travel behaviour of people and urban mobility patterns. Nonetheless, the impacts of these new mobility services on urban transport systems in terms of vehicle miles travel (VMT) is one of the controversial issues to be answered.

One of the significant concerns about these services is that they generate the additional vehicle miles travelled in urban networks due to empty trips. The measurement of empty vehicle miles travelled is extremely important to assess their impacts on congestion and associated vehicle emissions in cities because VMT is a fundamental measure of transportation system performance and has significant implications on the congestion level in the network. As the trips of ride-hailing services continue to increase across the world, understanding their effects on urban transport are becoming more crucial for researchers, policymakers and transport planners. Moreover, considered to future with an emergence of autonomous and connected vehicles, which is estimated to accelerate the usage of ride-hailing services, the importance of determining the impacts of these new mobility services on transportation is vital to shape future transportation systems. For these reasons, quantifying ride-hailing services efficiency in terms of capacity utilisation or determining deadheading rate is a critical factor in evaluating their impacts on VMT systemwide.

Nonetheless, up to the present, there is scant evidence on this subject due to the lack of open data, especially in the UK. Within this framework, the initial aim of this research was to investigate the transportation efficiency of private hire vehicle drivers across the UK by collecting primary travel data via surveys. However, the method of data collection was not approved by the Faculty Research Ethics Committee at the University of Leeds. Therefore, in the scope of this study, it was used an open dataset published by RideAustin, a non-profit ride-hailing company in Austin, including driver trip details during the period Uber and Lyft were temporarily out of service in the city.

The principal objectives of this research are:

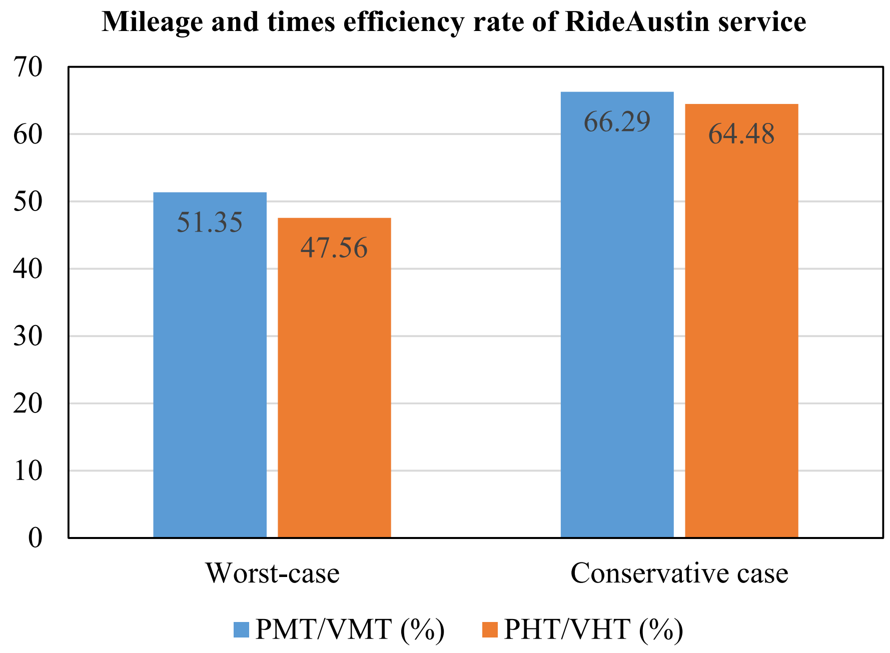
- To identify the ride-hailing service driver daily activity scheme and evaluate the possible scenarios of drivers;
- To develop the metrics by analysing individual ride-hailing driver trip data for determining the efficiency of drivers and the proportion of each segment in the scheme.

Contrary to prior research, this study presents the findings related to the efficiency ratio as a range value based on lower and upper limits. Upper limit represents the conservative case that drivers park their vehicles immediately after the previous ride ends and wait for the next ride request, or situation that request of next ride was dispatched to drivers before the previous ride ends. However, the lower limit for efficiency represents the worst-case scenario that drivers travel without parking until they reach passenger pick-up locations of the next ride. Based on the analysis method, it is expected that actual efficiency is within this range. The results presented here are based on 12,089 rides data, which are conducted by ten drivers who have the highest trip number from December 31, 2016, to March 31, 2017.

Based on analysis of RideAustin dataset, the following key findings can be highlighted:

- The mileage-based efficiency of RideAustin service is varying between 51.4% and 66.3%, excluding commuting segments of deadheading. This equates that for every 100 miles with a passenger, a ride-hailing driver has to travel an additional 51 miles with empty seats in conservative scenario case, while 95 miles in the worst-case scenario.
- Ride-hailing drivers can increase their efficiency by up to 29 per cent if they park immediately after the previous ride ends, thereby saving fuel consumption of their vehicles. (It was assumed that same requests were dispatched to drivers without considering closes to riders' locations)
- While considering times efficiency of ride-hailing services in terms of vehicle hours travelled, RideAustin efficiency rate is ranging between 47,6 % and 64.5%.
- Drivers spend more time without passengers than with one in the car, during their shift hours. The estimated deadheading time rate of RideAustin is 52.4 per cent for rides less than 60 minutes between each other.

- More than half of the next trips of drivers start within the 15 minutes that after their previous ride ends.
- The average waiting time for RideAustin service is almost 4 minutes, also drivers and passengers waste approximately an additional one and a half minutes at the pick-up locations before the ride starts.


Mileage and times efficiency rate of RideAustin service

- More than half of the riders use RideAustin services for travelling a short distance that is less than 4 miles. The average duration of trips is just over the 12 minutes, while the average trip length is 5.04 miles.
- Ride-hailing drivers spend roughly 44 per cent more time than trip duration for carrying passengers after the ride request.

In sum, the results of this study indicate that ride-hailing service generates a considerable amount of empty VMT on the streets. This effect would tend to increase VMT in the urban networks and thus, congestion and associated vehicle emissions. However, the overall impacts of these services on VMT is challenging to assess based on the current data because many parameters affect the VMT, such as model substitution, car ownerships and occupancy level. Apart from that, although RideAustin data have provided a basis for many significant types of research since they represent a single organisation, still there is a need to broaden the variety of data to obtain a more accurate result.

CHAPTER I

INTRODUCTION

1.1 Background

The latest developments in the information and communication technologies (ICTs) have affected people's daily life actions, including their travel behaviours. App-based on-demand transportation platforms such as Uber and Lyft are one of such examples which arise with the advanced developments in and extensive use of the smartphones and related applications (Wenzel et al., 2019; Henao and Marshall, 2018; Komanduri et al., 2018). In the literature, different names are given to these platforms such as ride-hailing, ride-sourcing, transport network companies (TNCs), commercial transport apps (CTAs), app-based rides and on-demand rides, among others (Henao, 2017). In England, ride-hailing is commonly referred to as a private hire vehicle (PHV) that provides hire a motor vehicle with the services of a driver to carry a maximum of nine passengers (DfT, 2011). In this study, "ride-hailing" term is preferred for referring to these mobility services.

Ride-hailing can be briefly defined as a system that provides profit-oriented on-demand rides services using smartphone applications. In a ride-hailing service, the application allows the connection between travellers who request a ride in real-time and potential nearby drivers willing to provide transportation. After a driver accepts the request, the app gives real-time information about the vehicle`s location and estimated waiting times for the passenger through the geographic information system (GIS). Riders can also learn estimated fare before the trips, but when there are more riders than available drivers, the actual fare is higher than expected due to the surge factor in order for balancing supply and demand. These services also allow the passengers to pay via credit card and enable both passengers and drivers to evaluate each other after the ride is completed (Rayle et al., 2016).

The evolution of transportation services and new terminology of mobility lead to confusion on the term of ride-hailing service and sometimes incorrectly used by the public (Henao and Marshall, 2018). However, it is essential to distinguish between different shared-mobility services, particularly when the evaluating of their impacts on urban mobility pattern (Clewlow and Mishra, 2017; Shaheen et al., 2016). Contrary to ride-sharing, ride-hailing drivers offer rides for profit rather than share the expenses of their own trip (Tirachini and Gomez-Lobo, 2019; Rayle et al., 2016). However, some applications allow passengers to share the ride and corresponding cost with strangers. In this case, the ride-hailing trip is referred to as ride-sharing (Wenzel et al., 2019). UberPool and LyftLine are examples of these services but are only available in certain cities. In the United States, the idea of car-sharing first started in 1997 in Portland, and in 2000, with the introduction of Zipcar and Flexcar, the system turned into a subscription-based carsharing program (Komanduri et al., 2018). The use of ride-hailing and ride-sharing services in the form of current services started about a decade ago with Zimride, which is an actual rideshare program, in 2007 (Henao, 2017). Then with the launching of UberCab in 2010 and Lyft in 2012 (Henao, 2017), these services have become more popular among people, especially in the U.S. According to the study of Smith (2016), it was estimated that 36% of the Americans (21% urban, 15% suburban) used ride-hailing services while 24% of them use these service at least once a week (as cited in Clewlow and Mishra, 2017).

Ride-hailing service is often distinguished from traditional taxi services by its use of smartphone app and dynamic supply-demand matching algorithm (Rayle et al., 2016). Although some taxis have also adopted this technology (e.g., yellow taxis in İstanbul), their patronage is still significantly smaller than ride-hailing. Another prominent difference is that ride-hailing services have been subjected to relatively light regulatory controls to operate compared to taxis which implies lower barriers to enter the market. In many states in the U.S., there is no limit for ride-hailing services on the number of vehicles, service price, geographic service restrictions, and safety standards such as driver training, vehicle inspections, or driver background check (Rayle, 2016; TRB, 2015). These advantages of ride-hailing services over taxis triggered the rapid growth in the transportation market and, consequently, disruptive change in the traditional taxi industry in many cities around the U.S. (Conway et al., 2018). A similar trend can be seen not only in the U.S. but in many cities around the world (Dudley et al., 2017; Nurhidayah and Alkarim, 2017; Zou, 2017).

This new mobility option has been growing steadily over the last few years, and this trend is expected to continue. As Uber, which is the largest ride-hailing service provider, announced that as of June 10, 2018, they had reached 10 billion rides, including Uber Eats trips (Uber, 2018). Likewise, Lyft, which is the second-largest ride-hailing service provider in the U.S., reported their first billion rides in September 2018 (Hondorp, 2018). Similarly, their Chinese counterpart Didi Chuxing reported that they are serving 25 million passengers in a day with 21 million drivers (Sreeharsha and Isaac, 2018). More strikingly, in 2018, Didi riders travelled almost 49 billion kilometres, and this equals to about five round trips from Earth to Neptune

(Zhang, 2019). Similarly, recent data from the Department of Transport show that the popularity of ride-hailing services has increased the number of licenced PHVs in London. This is because it rose by 25% from 2005 to 2013, while it increased by 75% from 2013 to 2017 (DfT, 2017).

The growing popularity of ride-hailing services around the world is mainly a result of the technological innovations that give travellers many advantages. Ride-haling services provide more reliable transport service with shorter waiting times to more locations and lower cost than traditional taxi services (Tirachini and Gomez-Lobo, 2019: Rodier, 2018; Rayle 2016). Also, ride-hailing services increase reliable car accessibility for travellers and neighbourhoods previously marginalised by limited access to expensive taxi services or private vehicles (Brown, 2018). Compared to traditional taxi and transit services, this new transportation option offers ease of payment and use, also provides a higher level of availability at all times of the day due to an ample supply of drivers (Schaller, 2017; SFCTA, 2017). Besides, not having to search and pay for parking and avoiding driving after drinking are other important reasons for customers to use these services, in particular for social and recreational rides (Clewlow and Mishra, 2017; Henao, 2017).

As anticipated, the prevalent adopters of this new app-based mobility service are the young population with a high ability to use technology. Survey-based research in U.S cities demonstrate that ride-hailing services are mainly used by younger people, have well-educated, lower car ownership and have a higher income than the average population (Alemi et al., 2018; Clewlow and Mishra, 2017; Henao, 2017; Rayle, 2016). Similarly, Schaller (2018) established that the use of ride-hailing services is higher among younger, more educated and more affluent residents, based on the National Household Travel Survey data. However, technology is also one of the barriers to access the ride-hailing services for low-income groups with low access to the smartphone, or for the elderly with little ability to use smartphones (Brown, 2018). Therefore, it is expected the number of riders continues to rise with the increasing the number of smartphone users across the elderly population. This is because ride-hailing may be a solution for future seniors to maintain their mobility after they are no longer drive.

More importantly, ride-hailing companies are investing and working together with car manufacturers for autonomous and connected vehicles technology. It is announced that the AV technology will be available to the transport market in the near future and it will start hauling passengers with self-driving vehicles on the street (Alvarez, 2019; Hawkins, 2019; UberATG, 2019; Scrutton, 2016). Indeed, Waymo has already started to carry passengers in the Phoenix area with fully autonomous vehicles, but it is on a small scale for the present (Welch and Behrmann, 2018). There is no doubt that the emergence of AVs on the mobility industry will trigger augmentation in the usage of ride-hailing services. Particularly, if ride-hailing services reduce the ride cost due to the elimination of driver fees, the patronage of ride-hailing services would rapidly grow because of increases the accessibility of low-income groups (Brown, 2018).

However, in parallel with the rapidly growing on-demand mobility industry in cities around the world, many questions have arisen about their role in urban transport. The impacts of these services on overall transportation systems, traffic congestions and associated environmental pollution are one of the controversial questions to be answered. Without a clear understanding of how ride-hailing services are and will be changing urban mobility patterns, city officials and transportation planners face a significant challenge in pursuing the goal of designing a more sustainable, equitable, and safe transportation system.

One of the widespread concerns about ride-hailing is that the use of these services leads to additional vehicle mileage on city streets because of empty trips. Ride-hailing services generate two types of trips: passenger rides that are transporting travellers between origins and destinations; and empty trips also known as deadheading trips that drivers are travelling when there is no passenger in the vehicle. Therefore, as the number of trips increases dramatically, measuring of empty vehicle miles travelled (VMT) that is generated by ride-hailing services becomes more vital to assess their impacts on congestion and associated vehicle emissions in cities. Because VMT is a fundamental measure of transportation system performance and has significant implications on the congestion level in the network.

The research in this dissertation is motivated by investigating the ride-hailing services efficiency rate based on capacity utilisation and thus, deadheading rate. In the literature, even though there is a number of studies pursued about the ride-hailing trips and users characteristics based on the user surveys, there is limited research available on empty trips and its impacts of ride-hailing services on urban transportation networks. (Henao and Marshall, 2018; Rodier, 2018; Nair et al. n.d.). This is because, as many researchers highlighted, there is a lack of open data source about the ride-hailing trips due to the reluctance of ride-hailing service providers to share trip data with the public (Henao & Marshall, 2018; Komanduri et al., 2018). As Henao (2017) stated perhaps companies do to avoid showing their potential negative impacts on the urban transportation system. This lack of meaningful data is preventing researchers from understanding and quantifying the impact of these services on VMT and regional travel patterns.

In 2016, a non-profit organisation RideAustin, which was launched after the ceasing of Uber and Lyft in Austin, has started to provide open data source to ensure the transparency and to support the researches (Komanduri et al., 2018). However, although RideAustin data have provided a basis for many significant types of research since they represent a single organisation, still there is a need to broaden the variety of data. Given the information in the background, the aim and objectives of this dissertation and the structure of the report are stated in the following sections.

1.2 Aims and Objectives

As the popularity of ride-hailing services continues to increase across the world, understanding their effects on urban transport are becoming more crucial for city officials and transport planners. One of the concerns about these services is that they are leading to increasing empty vehicle miles travelled in urban areas, thus on transport externalities such as congestions and air pollution. However, there is scant evidence on this topic due to the lack of open data. Within this framework, the primary aim of this research is to measure the transportation efficiency of ride-hailing services by analysing travel data, thereby to calculate the deadheading rate in terms of times and mileages. Indeed, the main aim of this study was to contribute to filling the current gap in the UK by collecting and analysing primary rides data from the PHV drivers at different cities in the UK. However, the method of data collection was not approved by the Faculty Research Ethics Committee at the University of Leeds. For this reason, in the scope of this study, it was used an open dataset published by RideAustin, which is a non-profit ride-hailing company in Austin, including driver trip details during the period Uber and Lyft were temporarily out of service in the city. Also, the findings of this study could be a key factor in understanding the possible impacts of future AVs.

The principal objectives of this research are:

- To identify the ride-hailing service driver daily activity scheme and evaluate the possible scenarios of drivers;
- To develop the metrics by analysing individual ride-hailing travel data for determining the efficiency of drivers and the proportion of each segment in the scheme.

1.3 Dissertation Overview

This dissertation report consists of five chapters and is organised as follow. Chapter I (Introduction) presents the background information about the main subject, problem statements, and the aim and objective of the research. Chapter II (Literature Review) overviews the topic of evolving transportation services and covers the limited literature. In Chapter III (Methodology), a brief description of data and sample size, and data analysis methods are introduced. Chapter IV (Results and Discussions) describes the results of the analysis and compares the findings of the study with literature. Chapter V (Conclusions) briefly summarizes the research and findings, explains the limitations of research, and gives the recommendations for further studies.

CHAPTER II

LITERATURE REVIEW

The ride-hailing and ride-sharing services have caused changes in the travel behaviour of people and urban mobility patterns. Today millions of people use these services both for regular daily commutes and recreational purposes. Therefore, as ride-hailing services become more and more popular among people, it is crucial to understand their impacts. However, since the field is relatively new, there is a limited number of studies regarding the ride-hailing services itself and the investigation of impacts of the ride-hailing services on transportation systems (Henao and Marshall, 2018; Komanduri et al., 2018; Wenzel et al., 2019).

In the earlier studies, ride-hailing services were compared with the traditional taxis. The study of Cramer and Krueger (2016) is an example of such studies. They carried out a comparative study to investigate the capacity utilisation rate of ride-hailing services and traditional taxis. They collected data for five major cities in the USA from related organisations. As a result, except New York, in other four cities (Boston, Los Angeles, San Francisco, Seattle) ride-hailing services have had averagely 49% and 61% higher time-based and mileage-based capacity utilisation rates than taxis respectively (Cramer and Krueger, 2016). In their study, Cramer and Krueger (2016) also discussed the unoccupied trips of both ride-hailing services and taxis and found that while 60% of total trip miles of taxis belonged to empty trips, this rate dropped to 36% in ride-hailing services.

Similarly, Rayle et al. (2016) carried out a survey-based study to compare the traditional taxi industry and ride-hailing services and to investigate the travel behaviour of service users in San Francisco. They collected data for the period of May-June 2014 with an intercept survey. In the study, in addition to demographic characteristics of service users, their trip origin-destination and trip purpose were also discovered. When ride-hailing services were compared with the traditional taxis, it was revealed that the shorter and more consistent waiting time and shorter travel time of ride-hailing services make them a more preferred alternative among passengers (Rayle et al., 2016). In the study, in addition to the taxi industry, the effects of ride-hailing services on other modes were also discussed. As a result, although it has had little impact on personal vehicle ownership, the existence of ride-hailing services has caused a shift from public transit due to the shortest travel time (Rayle et al., 2016). However, due to the time and location of the survey, the study sample did not reflect the whole population since it mostly reflected the response of people whose purposes were mainly social trips (Rayle et al., 2016). In other words, this research underestimated the commute trips.

Another survey-based study in seven major U.S. metropolitan areas showed that ride-hailing services likely lead to an increase in net VMT in cities (Clewlow and Mishra, 2017). This is because it was revealed that 49 per cent to 61 per cent of ride-hailing trips would have not been made at all, or by public transportation, or biking, walking. They also conjectured that the use of these services is associated with the average net 6 per cent reduction in overall public transit use in major cities. (Clewlow and Mishra, 2017). However, it was not conducted any analysis on empty trips and the authors emphasised that the net change in VMT is unknown.

In the research of Hampshire et al. (2017), they investigated the impact of ride-hailing services on travel behaviour and mode choices of people in Austin. They primarily worked on the mode shift and changes in the trip frequency after the cession of Uber and Lyft in the Austin region which helps to gain insight into the people's travel behaviour in the nonexistence of ride-hailing services. As a result of their study, they have found that after the disruption 45% of the Uber and Lyft users switched to use their personal vehicles, while only 3% of them shifted to public transits which (Hampshire et al., 2017). Although in their research, Hampshire et al. (2017) did not make any numerical calculations regarding the change in the trip frequency or total VMT, their research provides valuable findings for understanding the impacts of both existence and nonexistence of ride-hailing services.

In the study of the National Center for Sustainable Transportation, in order to understand the positive and negative impacts of ride-hailing services on VMT generation and GHG emissions, a framework was developed (Rodier, 2018). Within the scope of the study, by synthesising the framework and the findings from the available researches in the literature, the impacts of ride-hailing services were investigated. In the study, the findings of the previous researches were categorised under the five sub-headings of the framework and analysed to understand the effects of ride-hailing services on VMT generation and GHG emissions. The first important finding of the study is that with the ride-hailing services, 9% to 10% of the survey respondents have stopped using their private vehicles (Clewlow and Mishra, 2017; Rayle et al., 2016). In addition to that, it was found that with the existence of ride-hailing services, 8% to 22% increase has occurred in vehicle trips (Clewlow and Mishra, 2017; Henao, 2017; Rayle et al., 2016). Also, in the study, the effect of ride-hailing services on transit was investigated and it was revealed that there is a shift from public transit to ride-hailing (Rodier, 2018) which may have a serious impact on VMT generation and GHG emissions.

According to the results of other available researches that were carried out in different cities of the U.S., ride-hailing services have caused a 36% to 45 % increase in VMT (San Francisco Country Transportation Authority, 2017; Wenzel et al., 2019). Also, as San Francisco Country Transportation Agency reported, ride-hailing services in San Francisco have been responsible for the 10% of the VMT created in the period of 2010-2016 and 50% of the increase in traffic congestion (SFCTA, 2017). However, the results of another study revealed that if the ride-hailing services stop their operations, 50% of the service users who attend the survey stated their preference as starting to use private vehicles which will increase VMT and congestion, while only 3% of them will use public transport (Hampshire et al., 2017). However, these studies do not cover the share of commuting and deadheading, which refers to the empty trips that the drivers made without a passenger in the vehicle, in their methods which means that the actual impact of these services in VMT changes was not reflected in these studies (Wenzel et al., 2019).

Another significant study related to the VMT generation of ride-hailing services was carried out by the San Francisco Country Transportation Authority (SFCTA) in 2017. As a result of the study, it was revealed that 15% of the weekday trips were realised with the ride-hailing services which are 12 times more than the taxi trips and 15 times more than the trips with public transits (SFCTA, 2017). Also, while the ride-hailing services were responsible for the 20% total VMT generated during the weekday trips within San Francis city centre, this amount dropped to 6.5% when San Francisco was considered as a whole (SFCTA, 2017). However, this study has important limitations. First of all, in the estimations only the trips within the San Francisco city centre were taken into consideration, which means that a substantial part of the ride-hailing trips was not considered in this study. Secondly, the start and end locations of each trip were taken as the locations where the drivers accept rides and are available again. In other words, in this study the deadheading distances at the start and end of the trips were included as occupied trips which were actually the empty trips. Lastly, this study did not include the deadheading distances resulted from the drivers commuting. Therefore, although this research helps to gain insight into the contribution of ride-hailing services to congestion and VMT generation, due to the limitations mentioned above its approach to deadheading distances is too conservative to reflect the actual unoccupied VMT generation.

As many researchers agree, one of the most significant gaps in the literature of ride-hailing services is the lack of data related to this field (Henao and Marshall, 2018; Komanduri et al., 2018; Rodier, 2018). The main reason behind this is that the ride-hailing service provider companies are reluctant to share trip data because of privacy concerns (Komanduri et al., 2018). Due to the lack of sufficient data in the literature, in the study of Henao and Marshall (2018), one of the authors collected related data himself by working as a driver in two of the most well-known ride-hailing service companies and analysed these data in their researches. At the end of the data collection step of the study which is the most novel part of the study, the researchers have obtained two different datasets that are driver dataset which includes trip information and passenger dataset that is like regular on-board survey (Henao and Marshall, 2018). Different than the other researches mentioned above, the researchers especially emphasise the effect of deadheading. During the rides in the data collection step, the author/driver especially parked his vehicle at the end of each trip and tried not to take a passenger whose location is farther than 15 miles to driver's location in order to minimise the VMT generation due to deadheading (Henao and Marshall, 2018). As a result of their research, it was measured that 40.8% of the ride miles are made due to deadheading (Henao and Marshall, 2018). In other words, for every 100 miles with passenger, ride-hailing driver makes an additional 69 miles. Overall, according to the study of Henao and Marshall (2018), the existence of ride-hailing services causes additional 83.5% VMT in the system when compared to the nonexistence of these services (Henao and Marshall, 2018). However, although they have considered potential deadhead VMT sources since they have used a conservative approach to VMT generated due to deadheading and carried out their study based on the data collected from a singular driver, their results may not reflect the actual VMT generation of ride-hailing services.

In their study, Komanduri et al. (2018) focus on the system-level metrics and key performance indicators of ride-hailing services as well as the user profiles and travel patterns. Within the scope of their research, in addition to standard modelling metrics such as VMT, total travel times, and fares, they also calculated the deadheading time and distance, and terminal time by using the open dataset provided by RideAustin. In the calculation of deadhead distance, Komanduri et al. (2017) used the straight-line distance between the end and start points of two consecutive rides, which may reflect only the lowest value of the deadheading distance. While calculating deadheading distance and time, they made an assumption for deadheading at the start and end of each shift as 2 miles and 5 minutes based on their calculation of 2.15 average non-revenue miles travelled in the middle of the shift (Komanduri et al., 2018). However, it is worth to note that, since these metrics depend on the drivers' choices of start and end points, this assumption may not reflect the actual deadheading time and distance. As a result of their calculations, it was revealed that deadheading distances and times constitute approximately 37% of 8.7 million total VMT and 50% total travel time respectively. Another important finding from the study is that in the Austin region, passengers prefer these services to travel shorter distances (averagely 2.5 to 3.5 mile) and mostly in specific times. Additionally, it is also worth to mention that in their studies, Komanduri et al. (2018) investigated the transit competitiveness with a case study. As a result, they found that people who do not have another mode choice or require more than 2 transfers constitute 14% of the RideAustin passengers.

In the study of Wenzel et al. (2019), they have used 1.5 million trip data provided by RideAustin as publicly-available to investigate the net change in the VMT generation. By using this data, they analysed the trips on a monthly, daily, and hourly basis. In their studies, they also considered the contribution of the commute and deadhead distances in VMT change. In the calculation of deadheading distances, they used the straight-line method with an estimated adjustment factor of 1.4 for the actual length of the street networks. Also, to calculate the energy use, they estimated the modal shift to ride-hailing services by utilising two rider surveys from the literature. They found that deadheading percentage of RideAustin services is 45 per cent, 26 per cent corresponds to between rides, and 19 per cent to commuting. The authors concluded that the net effect of ride-hailing on energy use is a 41% to 90% increase compared to prior travel mode.

In light of the findings from the literature review, the gaps in the literature were determined. In the next chapter, the data source and sample size of this study were stated, also it was explained the way of how to this data analyses in order for measuring ride-hailing efficiency rate. Contrary to previous studies, ride-hailing productivity rate and thus deadheading rate in terms of times and mileage were measured as a range value.

CHAPTER III

METHODOLOGY

3.1 Data Source and Sample Description

Initially, this study was planned to collect and analyse primary rides data directly from the Private Hire Vehicle (PHV) drivers at different cities in the UK. Unfortunately, I could not get permission from the University of Leeds`s Social Sciences, Environment, and LUBS (AREA) Faculty Research Ethics Committee to collect the primary data by means of planned survey method. After the committee's decision, the practices of analysis were changed and made suitable for secondary data in order to continue the research.

Various public datasets were compiled to conduct research about the impact of traditional taxi and ride-hailing services on transportation with different perspectives. However, quite limited datasets are publicly available to undertake the analysis of transportation efficiency of ride-hailing services by considering empty trips. In particular, no data has been shared in the UK to date by PHV companies or transport authorities. For this reason, RideAustin data, which is one of the most valuable publicly available datasets, was used in this study to measure ride-hailing efficiency. The database was created by RideAustin, a non-profit TNC operating in Austin, Texas. RideAustin entered the ride-hailing market in 2016, shortly after the two market leaders Uber and Lyft shut down their operations in Austin because of disagreements over local regulations about fingerprint background checks[1]. The database consists of a total of 1,494,125 rides that are conducted by approximately 5,000 drivers for a period of 11 months from June 4, 2016, to April 13, 2017 (RideAustin, 2017). The RideAustin data provides individual trip level information, including the location of trip origins and destinations, recorded trip length, and corresponding fare. The RideAustin data also provides the timestamp at following five points along each ride: 1. when the ride request was dispatched to a driver; 2. when the driver accepted the dispatched request; 4. when the driver reached the passenger pick-up location; 3. when the ride started; and 5. when the ride was completed (Wenzel et al., 2019). To protect the privacy of their passengers, the coordinates of where the ride started and ended have been rounded by RideAustin to three decimal places. This degree of precision identifies passengers pick-up and drop-off locations only to within roughly 100 meters (Komanduri et al., 2018).

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[1] After the residents of Austin voted against Proposition 1 in May 7, 2016, Uber and Lyft suspended their services in the city. Because ride-hailing companies were obliged to perform fingerprint background checks on drivers and not allowed to use their own systems. This rule already applies to taxi companies in Austin (Hampshire et al., 2017).

In this dataset, it is possible to analyse the travel patterns of each of the drivers by aggregating individual rides which are identifiable with respect to the drivers. In addition, drivers' vehicle is also identified, including the brand of vehicle, model year, and, vehicle model. This feature of the dataset provides an opportunity to measure the efficiency of ride-hailing service in terms of vehicle miles travelled or energy consumption on driver level. This is why RideAustin dataset is different from other taxi and TNC trip datasets such as New York and Chicago.

In this study, as the number of riders during the first few months was limited, for example, more than half of the total trips occurred within the last 4 months, the analysis only includes data from December 31, 2016, to March 31, 2017. In other words, the analysis of this trip segment excludes data prior and after those dates. However, the data size of this period is quite large, so it is difficult to make an analysis using all the data within a limited thesis time. For this reason, this study focuses only on 12,089 rides data, which are conducted by 10 drivers who have the highest trip number over the total 734,482 rides in the ride-hailing service. This means that analysis bases on the most effective 10 full-time RideAustin drivers in terms of passenger carrying numbers during this period. The ID and vehicle and corresponding trips details of the identified 10 drivers are summarised in Table 3.1. The table shows that all drivers carried more than a thousand passengers during the 91 days period, ranging from 1,069 to 1,636. Another critical point is that although there are no significant differences between total trips of drivers, average trip numbers per working day are varying between 13.37 and 20.16.

Table 3.1 Drivers` vehicles information and trip details

Driver ID	Colour	Brand	Model	Year	Total Trips	Working Days	Average Trips per Day
357	Black	Toyota	Corolla	2016	1,232	78	15.80
654	Blue	Nissan	Versa	2013	1,174	78	15.05
846	Grey	Nissan	Pathfinder	2014	1,085	62	17.50
931	Grey	Ford	Explorer	2013	1,098	74	14.84
1078	Silver	Toyota	Corolla	2010	1,220	88	13.86
1991	Blue	Lincoln	Town Car	2002	1,636	87	18.81
2136	Red	Honda	Accord	2015	1,150	86	13.37
2372	Silver	Tesla	Model S	2013	1,296	85	15.25
2456	Black	Honda	Civic	2015	1,069	78	13.71
3775	White	Toyota	Camry	2011	1,129	56	20.16
Total					12,089	772	15.66

Figure 3.1 shows the distribution of weekly rides of each driver. The figure indicates that although the number of weekly rides remarkably changes for the 13 weeks, the drivers have a similar trend over the last 4 weeks. It is thought that Driver 357 did not work for the first week, similarly, Driver 3775 started riding as the RideAustin driver after the fourth week.

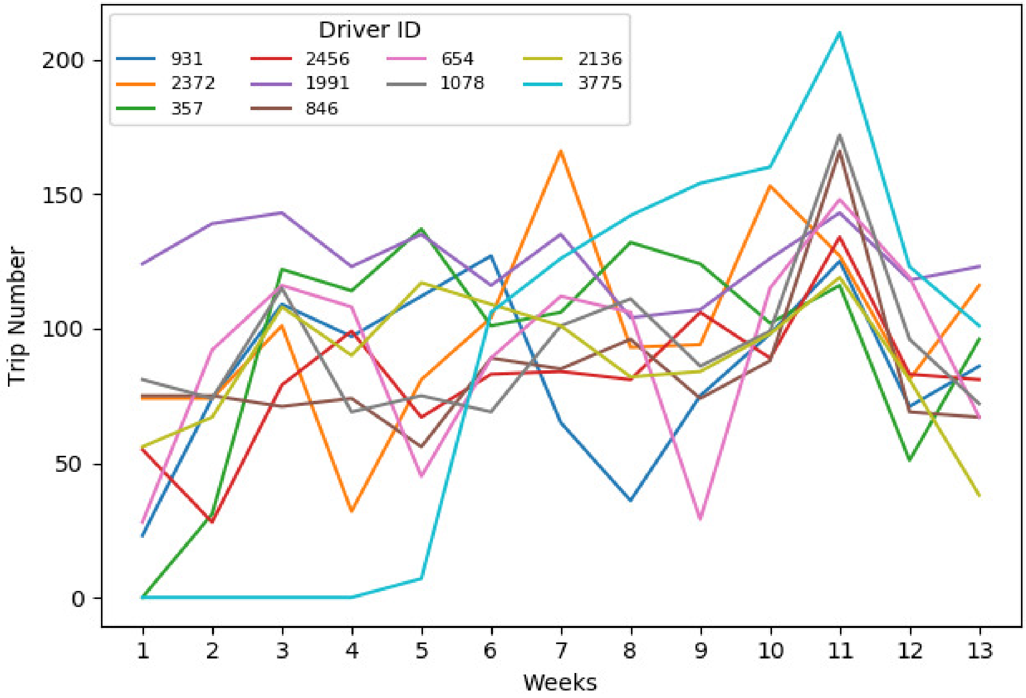

Figure 3.1 Weekly trip number according to drivers

Figure 3.2 displays the weekly distribution of total rides made by 10 drivers. As it can be seen in the figure, the weekly distributions of total rides fluctuated between 500 and 1400 rides, where the average number of weekly rides is around 930 rides. The peak on March coincided with the major event the South by Southwest festival that is held in Austin on mid-March every year. City of Austin data on traditional taxicab trips in previous years demonstrates that the number of taxi trips in Austin has reached the peaks on March and October as consistent with the findings presented above (Wenzel et al., 2019). This suggests that the majority of the RideAustin trips are taken for entertainment or recreational purposes, rather than as part of a regular school or business commute. This is consistent with Komanduri et al.'s finding (2018) that nearly 60% of all RideAustin trips are made from 6:00 p.m. to 6:00 a.m. In a similar manner, the results of survey-based studies in the US major metropolitan areas show that majority of the ride-hailing service users prefer these services mostly when they are travelling for social and leisure purposes (Clewlow and Mishra, 2017). Indeed, Lavieri et al. (2018) recently analysed the spatial distribution of RideAustin trips and identified the same pattern.

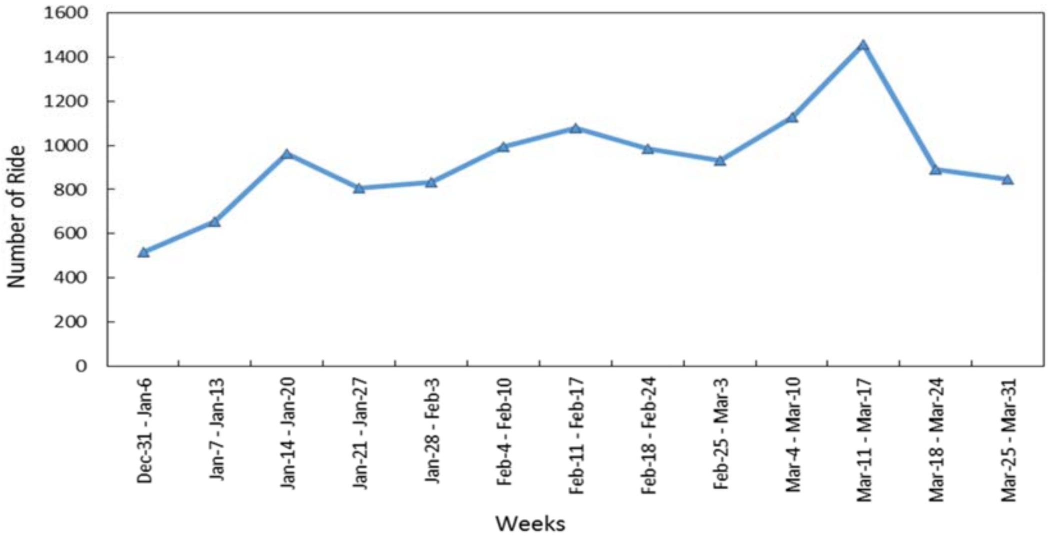

Figure 3.2 Total number of rides, by week

Before moving on to the data analysis section, in addition to the weekly distribution of trips number, understanding the where the trips were generated and distributed in Austin is significantly important in order to reveal whether the data of the ten drivers are representative. This is also essential to able to make healthy inferences on the efficiency of RideAustin service. Within this framework, passenger pick-up and drop-off location coordinates were supplemented using Zip Code data, including Austin city centre and surrounding suburban areas, obtained from the Capital Area Metropolitan Planning Organization (CAMPO) website.[2,3] Location data were mapped to the Austin region Zip Code defined by CAMPO using commercially available GIS software ArcGIS Map.[4] The spatial distributions of trip origins and destinations are presented in Figure 3.3 (described in detail in Appendix A). As can be seen in the figure, there is a clear concentration of trips in central and denser areas where are located in the centre of the figure consisting of relatively small polygons. Another important inference is that lots of rides started in the city-centre and ended in the suburban areas. Based on the spatial distribution, data conducted by 10 drivers may represent the RideAustin service because trips did not concentrate on specific zones and distribute to almost all areas in the city. It is worth to note that the drivers working habit (i.e. log-in the application and waiting for a passenger at the same zone for each shifting) can affect the analysis. However, a clearer outcome can only be obtained by evaluating the distribution of the origin location of the first ride of each shift (see Appendices A).

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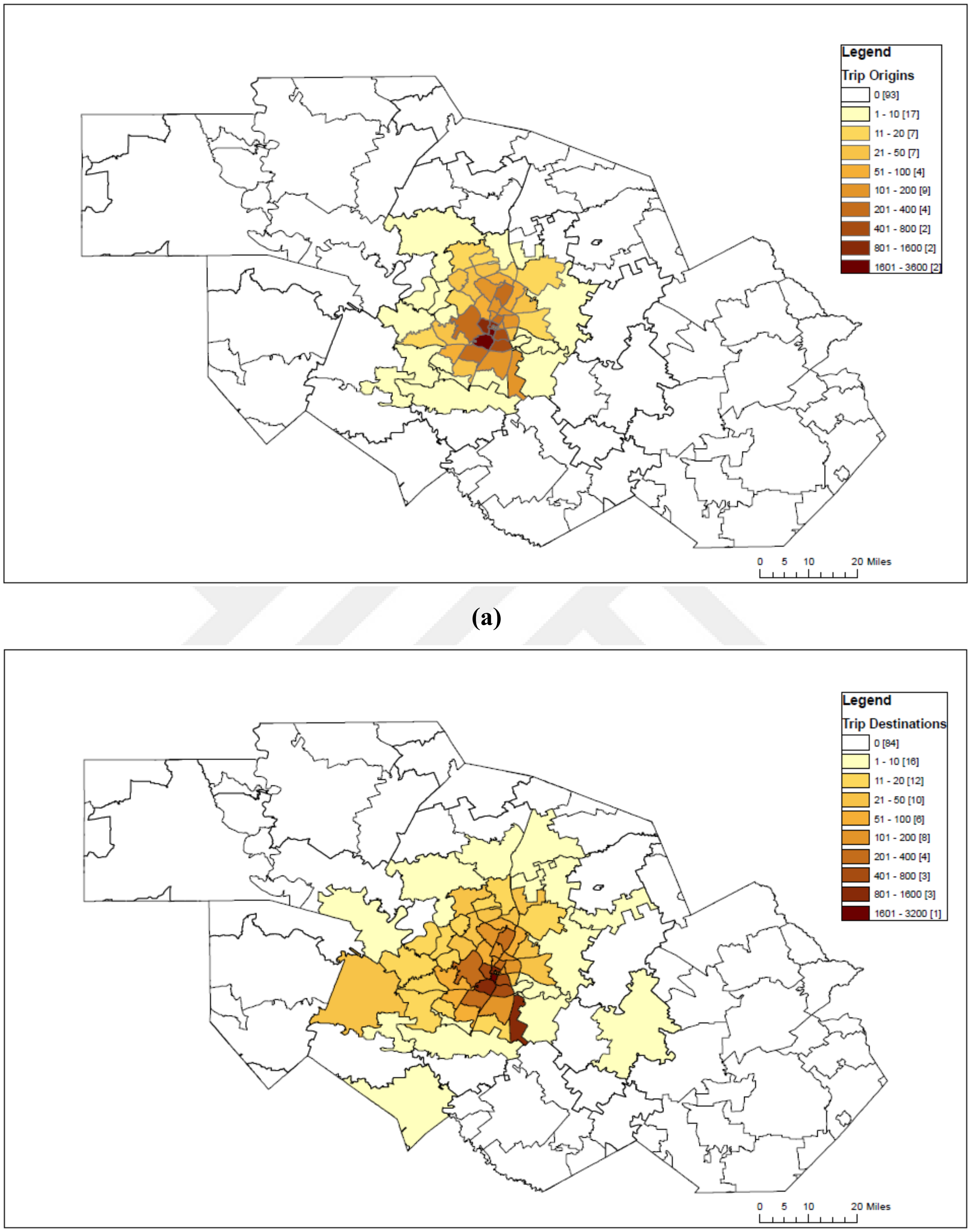
[2] Source: http://regional-open-data-capcog.opendata.arcgis.com/search?tags=Administrative%20Boundaries

[3] CAMPO is the Capital Area Metropolitan Planning Organization in Texas, which consists of Bastrop, Burnet, Caldwell, Hays, Travis, and Williamson Counties.



(a)

(b)

Figure 3.3 Spatial distribution of trip origins (a) and trip destinations (b) for a total of ten drivers according to Zip Codes

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[4] The Travel Analysis Zones (TAZs) data were not preferred in this study because rounded location coordinates may affect the results when using smaller areas boundaries.

3.2 Analysis Methods

This section consists of three sub-sections covering the specific method to calculate ride-hailing travel distance and duration, efficiency rate range, and fare productivity in terms of mileage and time. Ride-hailing efficiency rate and fare productivity analysis highly depend on the results of travel distance and duration analysis, in other words, without determining the travel pattern of drivers and corresponding values it is impossible to measure efficiency and fare productivity.

3.2.1 Ride-hailing Travel Distance and Duration

As it was mentioned earlier, travel patterns of each of the drivers can be constituted by aggregating the individual trip data. The basic daily travel pattern of the RideAustin drivers is shown schematically in Figure 3.4. According to Henao (2017), the components of the drivers` travel pattern are divided into two categories: deadheading and passenger (O-D) ride. The term deadheading refers to the distance travelled without passengers or freight and it is often used for the taxi and trucking industry (Henao and Marshall, 2018). Exclusive to ride-hailing services, there are four specific segments of deadheading which can be listed as commuting from driver residence; cruising for a ride; from dispatch to the pick-up location (it is also known as over-heading); and commuting at the end of shift. Based on the RideAustin data, it is not possible to figure out all deadheading segments in the travel pattern of drivers. As a consequence of this situation, this study includes some limitations in the methods of analysis and hence, some assumptions were made in order to continue the analysis.

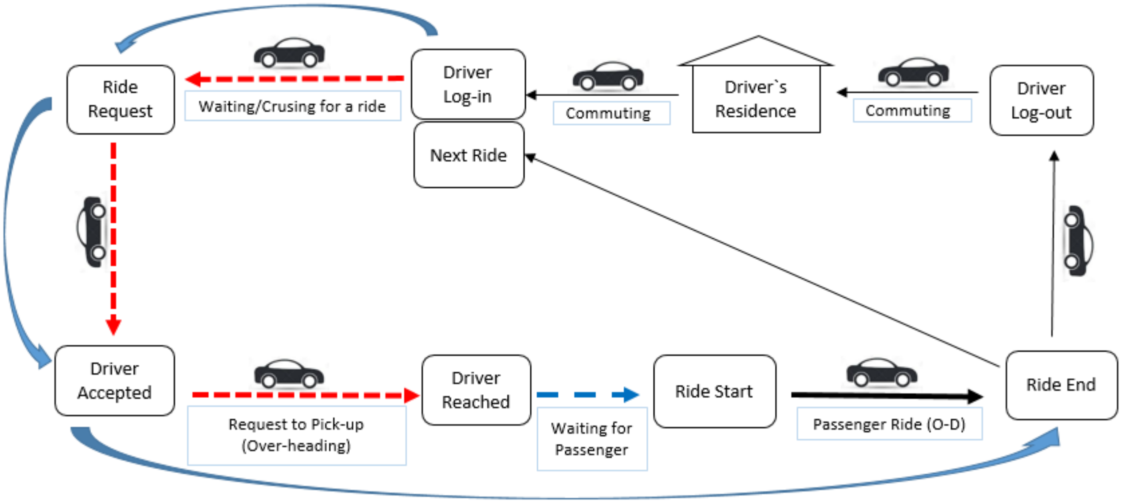
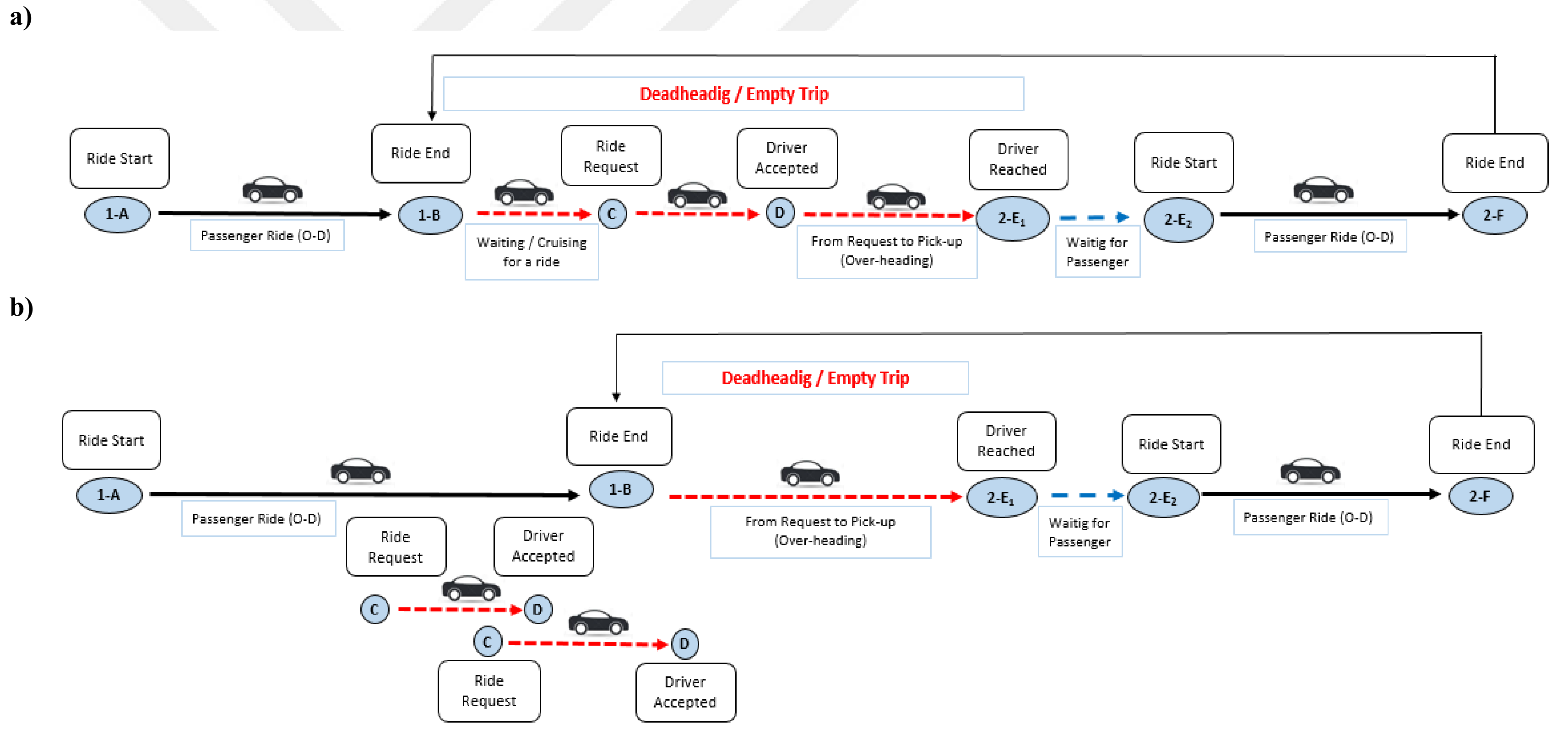


Figure 3.4 Ride-hailing driver`s daily working progress

One of the limitations of this study is that the commuting segments, that is the drivers travel without passengers at the start and end of shifts, cannot be determined since drivers` residence addresses were not provided in the dataset due to privacy reasons. Henao and Marshall, (2018) emphasise that the commuting segments, which are often overlooked, are important to better understand the actual impact of ride-hailing services on VMT and energy consumption. Wenzel et al.'s (2019) study on RideAustin data reveals that the average commuting distances for pre-shift and post-shift, based on the estimated driver's home location, are 5.3 miles and 7.2 miles respectively. However, these results are based on the assumptions that drivers turn on the RideAustin app at their residence at the start of their shift and turn off the app at their last passenger drop-off locations at the end of their shift. Similarly, Komanduri et al, (2018) assumed that drivers travelled two miles and five minutes for commuting of each shift. Unlike previous research (Wenzel et al., 2019; Henao and Marshall, 2018; Komanduri et al.,2018), this study focuses on driver travel pattern in-between time when the first ride request was dispatched to a drive and when the last ride was completed. In other words, commuting parts are not considered in the methodology of this study because of insufficient information.

Travel segments of RideAustin drivers between two rides and corresponding information on locations and time according to the dataset are shown in Figure 3.5. As it is seen from Figure 3.5, two different scenarios are possible for deadheading according to time when the ride request was dispatched to the driver. The first scenario represents the most common situation for ride-hailing drivers that new ride request is dispatched to the driver after the previous ride ends. In this case, after the previous ride ends drivers follow these patterns respectively: cruising for a new ride or wait for the new ride request while parking; ride request is dispatched to drive; ride request is accepted; travelling to a passenger pick-up location. If drivers do not prefer parking after the previous ride end, duration of vehicle miles travelled without passengers in other words empty trip duration is represented by the time period from previous ride ends to reach on the new ride origins. Moreover, distance travelled between this period represents the maximum empty trips distance. The second scenario represents the new ride request is dispatched to drivers before the end of the previous passenger ride. Drivers can accept this ride request during the current ride or just after the ride was completed. In this situation, drivers know where to travel after the current ride ends. This eliminates the cruising for a ride segment of deadheading and represents the conservative empty trip case. The time between previous passenger ride ends and reached on the passenger pick-up location represents to empty trip duration, while the distance between these two locations represents to empty trip distance.



Locations;

1-A: Passenger Pick-up Location for Ride 1
1-B: Passenger Drop-off Location for Ride 1
2-E: Passenger Pick-up Location for Ride 2
2-F: Passenger Drop-off Location for Ride 2

Time When;

1-A: Ride 1 Start
1-B: Ride 1 End
C: Request for Ride 2
D: Driver Accepted on Passenger Request of Ride 2
2-E$_1$: Driver Reached on Pick-up Location of Ride 2
2-E$_2$: Ride 2 Start
2-F: Ride 2 End

Figure 3.5 Travel segments of a RideAustin Driver between two rides; a) request time after previous ride; b) request time before previous ride end

Another limitation of this study is that given RideAustin data, the distances drivers travel without passenger between rides cannot be measured exactly. This is because GPS based data is required to measure how many miles travelled during deadheading periods. Although RideAustin database provides GPS measured distances for over-heading segments that is the distance travelled between the time when the driver accepted the ride request and when the driver reached the ride origins, this is not sufficient to determine real empty trip distance. This information was not considered in the methodology of this study since analysis aims to find a range for empty trips, which is based on the maximum and conservative vehicle miles travelled. However, this information was considered in Appendix D to show deadheading miles detailly.

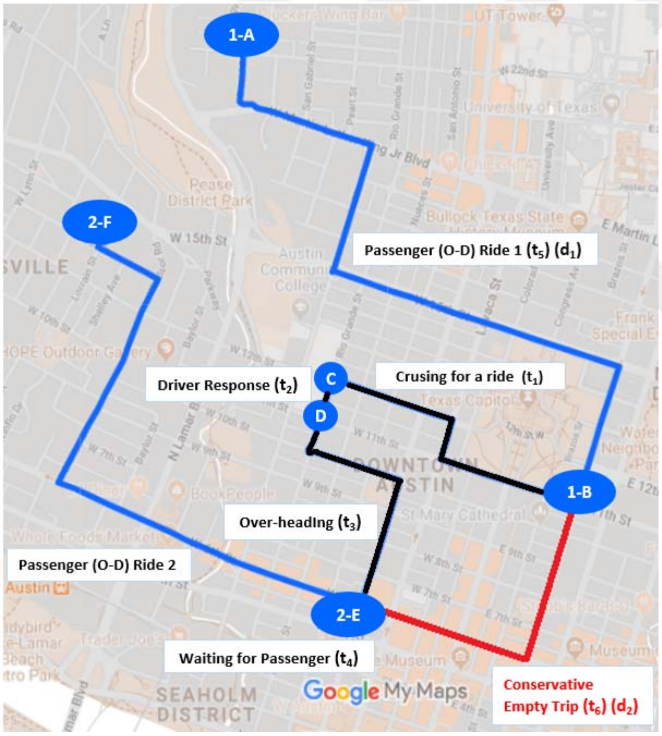


Figure 3.6 Components of sample two consecutive trips

Components of sample two consecutive rides are displayed in Figure 3.6, which illustrates how conservative empty trip miles are estimated in this study. Since locations where the driver when the ride request was dispatched (C) and when the dispatched request was accepted (D) are unknown, conservative empty trip distances between rides were measured by getting directions from previous ride`s passenger drop-off locations (1-B) to next ride`s passenger pick-up locations (1-E) by means of Google Maps. This is indicated by the red line in the figure. These analyses for ten drivers were performed by using Google Distance Matrix API key in Python, therefore, empty trip lengths reflect the street network distance. The distances between two locations and estimated duration travelling by car between these distances were obtained at the end of this step. This represents a potential strategy that drivers park just after completing each ride and wait for the next request, instead of cruising around to reduce the empty trip distance (Kontou et al., 2019; Henao, 2017).

Calculating the maximum empty trip distance, it is assumed that drivers travel during the whole empty trip period without parking, is indicated by the black line in Figure 3.6. Since drivers have to travel between two rides, the maximum empty trip distance was determined by the summation of conservative empty trip distance and additional VMT that is explained in the next section also detailly in Appendix B. As was mentioned in the previous section, RideAustin data includes the timestamp at five points along each ride. This provides an opportunity to calculate durations of all segments in the driver`s travel pattern to be analysed. Figure 3.7 shows the analysis of driving travel segments and corresponding duration and distance terms.

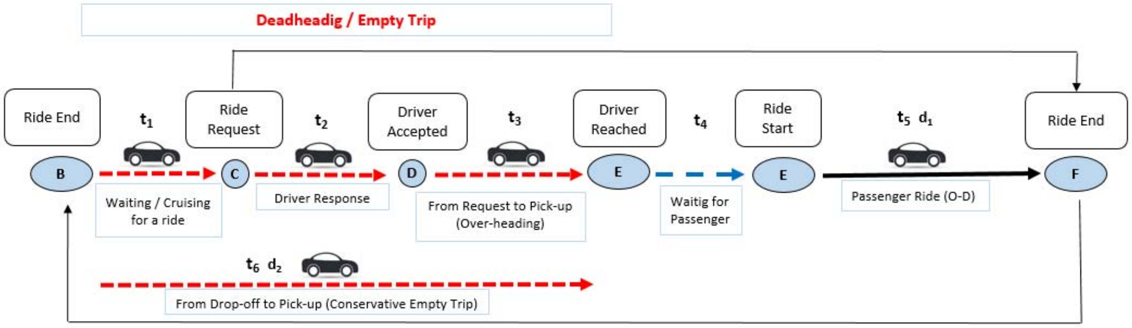


Figure 3.7 Analysis driving segments, with empty trip segments shown in red line

The distance and duration terms of ride-hailing components in the figure are explained in the below:

- t_1 = time from the previous ride was completed to when the next ride request was dispatched to a driver (Waiting or cruising for a ride)
- t_2 = time from ride request was dispatched to a driver to driver accepted the dispatched request (Driver response)
- t_3 = travel time from ride request location to passenger pick-up location (Over-heading)
- t_4 = waiting time for a passenger at pick-up location (Waiting for passenger)
- t_5 = travel time from the passenger pick-up location to drop-off location (Passenger (O-D) ride duration)

- t_6 = travel time from previous ride end location to next ride start location (Empty trip duration based on Google Maps)
- d_1 = travel distance from the passenger pick-up location to drop-off location (Passenger (O-D) ride distance)
- d_2 = distance from previous ride end location to next ride start location (Empty trip distance based on Google Maps)

Given time and distance terms above, ride distances and durations, and important parameters, which are used in the calculation of ride-hailing efficiency rate and fare productivity, are calculated by following equations for each driver for each shift *i* and ride j:

$$Total\ Empty\ Duration = \sum_{i=1}^{n}\left(\sum_{j=2}^{m} t_{1(i,j)} + \sum_{j=1}^{m} t_{2(i,j)} + t_{3(i,j)} + t_{4(i,j)}\right) \tag{1}$$

where *m* is the last ride of each shift *i* and *n* is the last shift;

$$Total\ Passenger\ Ride\ Duration\ (PHT) = \sum_{i=1}^{n}\sum_{j=1}^{m} t_{5(i,j)} \tag{2}$$

$$Vehicle\ Miles\ Travelled\ with\ Passenger\ (PMT) = \sum_{i=1}^{n}\sum_{j=1}^{m} d_{1(i,j)} \tag{3}$$

$$Unoccupied\ Vehicle\ Hours\ Travelled\ (UVHT) = \sum_{i=1}^{n}\sum_{j=2}^{m} t_{6(i,j)} \tag{4}$$

$$Unoccupied\ Vehicle\ Miles\ Travelled\ (UVMT) = \sum_{i=1}^{n}\sum_{j=2}^{m} d_{2(i,j)} \tag{5}$$

$$Total\ Empty\ Trip\ Duration = \sum_{i=1}^{n}\left(\sum_{j=2}^{m} t_{1(i,j)} + \sum_{j=1}^{m} t_{2(i,j)} + t_{3(i,j)}\right) \tag{6}$$

If empty trip duration based on Google Maps is higher than the total empty time between rides, total empty trip duration (Eq. 6) was taken as empty trip duration (UVHT). In other words, whichever value is smaller is taken as an empty trip duration. Apart from that, since analysis focuses on the period from first ride request time to last ride ends of each shift, "j" starts from the second trip of each shift for the empty trip and cruising parts.

3.2.2 Ride-hailing Efficiency Rate

In this section, the ride-hailing efficiency rate is calculated as a range value that is presented by the upper and lower boundaries in terms of both times and mileage. The upper limit represents the conservative case scenario that is based on the minimum travelling, while the lower limit represents the worst-case scenario that is referred to maximum travelling between rides.

Times Ride-hailing Efficiency Rate

To determine the time efficiency rate range, the summation of vehicle hours travelled with passengers (PHT) is compared to against total vehicle hours travelled for both conservative and worst-case scenarios. For time efficiency calculations, worst-case scenario represents the drivers do not cut off their vehicle`s engine during the period in between rides, and it is calculated by using the following equations:

$$Time\ Ride\_hailing\ Efficiency\ (Lower) = \frac{PHT}{Maximum\ VHT} \tag{7}$$

where:

$$Maximum\ VHT = PHT + Total\ Empty\ Duration \tag{8}$$

For the upper limit of ride-hailing efficiency:

$$Time\ Ride\_hailing\ Efficiency\ (Upper) = \frac{PHT}{Minimum\ VHT} \tag{9}$$

where:

$$Minimum\ VHT = PHT + \ UVHT \tag{10}$$

Mileage Ride-hailing Efficiency Rate

The mileage efficiency rate range is determined by comparing the summation of vehicle miles travelled with a passenger (PMT) versus total vehicle miles travelled for both conservative and maximum travelling case scenarios. The lower limit is calculated by using Equation (11).

$$Mileage\ Ride\_hailing\ Efficiency\ (Lower) = \frac{PMT}{Maximum\ VMT} \tag{11}$$

where:

$$Maximum\ VMT = PMT + \ UVMT \ + Additional\ UVMT \tag{12}$$

$$Additional\ UVMT = \frac{PMT}{PHT} \times (Total\ Empty\ Trip\ Duration - UVHT) \tag{13}$$

For upper limit of ride-hailing efficiency:

$$Mileage\ Ride\_hailing\ Efficiency\ (Upper) = \frac{PMT}{Minimum\ VMT} \tag{14}$$

where:

$$Minimum\ VMT = PMT + UVMT \tag{15}$$

3.2.3 Ride-hailing Fare Productivity

This section focuses on the fare productivity of ride-hailing service in terms of both mileage and times and describes the analysis methods of fare productivity calculation. Ride-hailing fare productivity is calculated by using total fare of all trips divided by the corresponding travel time or distance. Total fare calculation for each trip was explained by RideAustin dataset as follows:

$$Total\ Fare = \Big(\big((Base\ Fare + DistanceFare + Time\ Fare) \times Surge\ Fare\big) + Booking\ Fee\Big) \times 1.01^{*} \tag{16}$$

For this study, the ride-hailing fare productivity is determined by using the following equations:

$$Fare\ per\ ride\ minute\ \left({}^{\$}/_{min}\right) = \frac{\sum Fare}{PHT} \tag{17}$$

$$Fare\ per\ ride\ mile\ \left({}^{\$}/_{mile}\right) = \frac{\sum Fare}{PMT} \tag{18}$$

$$Fare\ per\ minute\ \left({}^{\$}/_{min}\right) = \frac{\sum Fare}{PHT + Total\ Empty\ Duration} \tag{19}$$

$$Fare\ per\ conservative\ mile\ \left({}^{\$}/_{mile}\right) = \frac{\sum Fare}{PMT + UVMT} \tag{20}$$

$$Fare\ per\ maximum\ mile\ \left({}^{\$}/_{mile}\right) = \frac{\sum Fare}{PMT + UVMT + Additional\ UVMT} \tag{21}$$

Given the calculations above are explained in more detail on the results section.

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* 1% is the fee to the city and it is included in the total fare of rides

CHAPTER IV

RESULTS AND DISCUSSION

In this chapter, the results of data analysis are provided and compared to other relevant researches in the literature. Analysis results are provided in divided section into three subsections covering characteristics of ride-hailing passenger rides, ride-hailing efficiency rates, and fare productivity.

4.1 Passenger (O-D) Trips

Passenger (O-D) ride characteristics in terms of trip distance and duration are easily determined by analysing RideAustin database. Figure 4.1 shows the distribution of the number of RideAustin rides by distance intervals in miles. The figure also displays the cumulative distribution of passenger rides. As it can be seen in the figure, 46 per cent of total 12,089 trips were completed less than 3.0 miles. Considering the long-distance trips, approximately 15 per cent of trips were travelled higher than 10 miles distance. These results suggest that the majority of RideAustin users prefer this service for short-distance trips. However, it should not be overlooked that analysis results in this study are based on the data collected by the top ten drivers who reached the highest trip number from 31 December 2016 to 31 March 2017. Therefore, results do not reflect all rides in Austin.

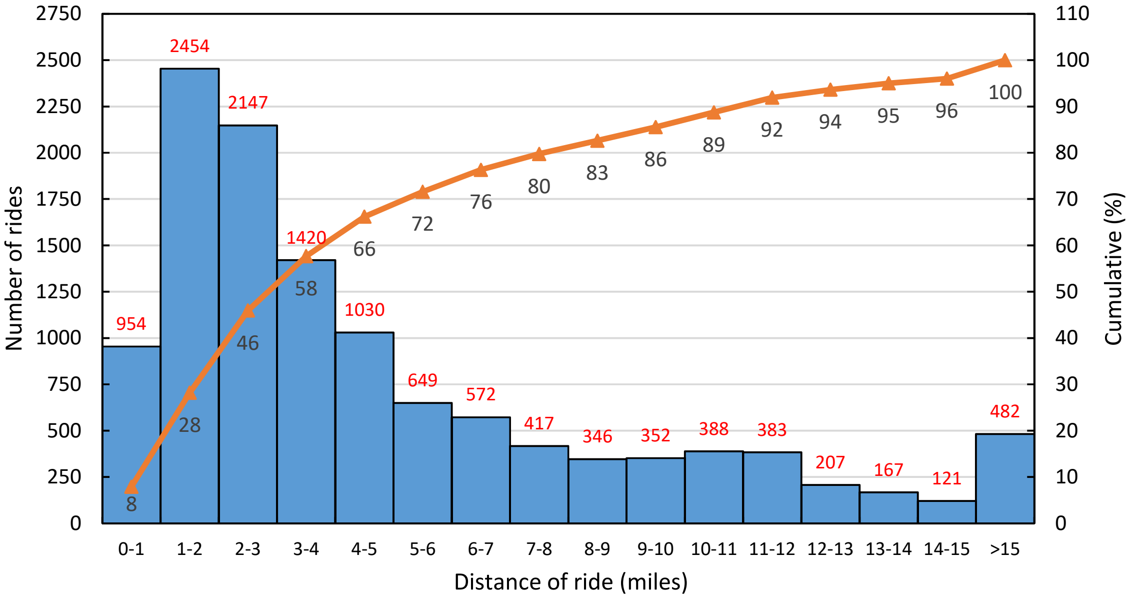


Figure 4.1 Distribution of passenger (O-D) ride distance

Table 4.1 illustrates the average trip distance and corresponding statistics according to drivers. The results are shown in Table 4.1. indicate that the average trip length is 5.04 miles for RideAustin. On the driver level, the average trip distance varies from 4.39 miles to 6.21 miles. These results differ from Komanduri et al.'s (2018) findings, but they are broadly consistent with the results of the study of Wenzel et al. (2019). Wenzel et al. (2019) found that the average distance of RideAustin trips between October 27, 2016, and April 13, 2017, is 5.4 miles. In contrast, Komanduri et al. (2018) found it is below 3.80 miles for this period. Compared to other regions in the U.S, results show differences because each area has unique characteristics in terms of transport and ride-hailing users. San Francisco County Transportation Authority`s (2017) report reveals that average intra-city trip lengths of TNCs are 2.6 miles for weekdays and Saturday, while 2.9 miles for Sunday. According to the results of another study that was carried out by Rayle et al. (2016), it was found that average ride distance is 3.2 miles in San Francisco, based on 380 surveyed ride-hailing trips collected in spring 2014. For Denver, this was measured as 7.04 miles, based on 416 trips data (Henao, 2017). Overall, these results support the Schaller`s (2018) findings. He indicated that ride-hailing trips length is typically 6.1 miles in American Cities and trips in large, densely-populated metro areas tend to be shorter (4.9 miles). On the other hand, trips in suburban and rural areas tend to be somewhat longer in the distance (8.7 miles).

Table 4.1 Trip distance summary statistics according to drivers

Driver ID	Number of Rides	Total Distance	Mean	Std. Dev.	Median
		(miles)			
357	1,232	5,410.07	4.39	4.66	2.69
654	1,174	5,433.70	4.63	4.53	3.10
846	1,085	5,658.74	5.22	5.19	3.27
931	1,098	5,812.53	5.29	4.82	3.49
1078	1,220	7,577.35	6.21	6.78	3.94
1991	1,636	7,375.86	4.51	4.33	3.00
2136	1,150	6,247.80	5.43	4.41	3.80
2372	1,296	6,318.90	4.88	5.01	3.33
2456	1,069	5,906.79	5.53	5.07	3.69
3775	1,129	5,231.39	4.63	4.47	3.15
Total	12,089	60,973.12	5.04	4.99	3.31

In this section, in addition to the trip distance, the duration of RideAustin rides was also investigated. Figure 4.1 display the number of RideAustin rides according to the time intervals in terms of minute, also shows the cumulative distribution of those rides. As can be seen in

Figure 4.2., the vast majority of the passenger rides (74%) was completed less than fifteen minutes. Moreover, it can be clearly observed that a third of the trips were completed between 5 and 10 minutes. Figure 4.3 displays the average ride duration according to driver level and to total drivers as well. The average trip duration was calculated as 12 minutes and 14 seconds for RideAustin, shorter than the average ride duration of 15 minutes in Denver (Henao, 2017). Another inference from the figure is that average trip durations do not show significant differences between drivers (see Appendix C for detail information about durations).

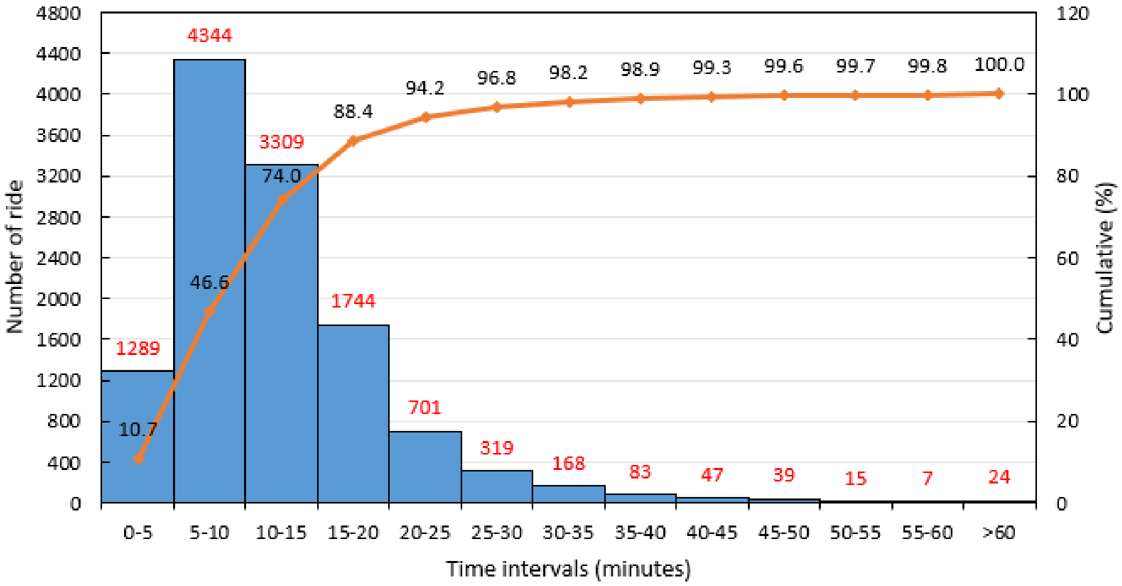


Figure 4.2 Distribution of passenger (O-D) ride duration

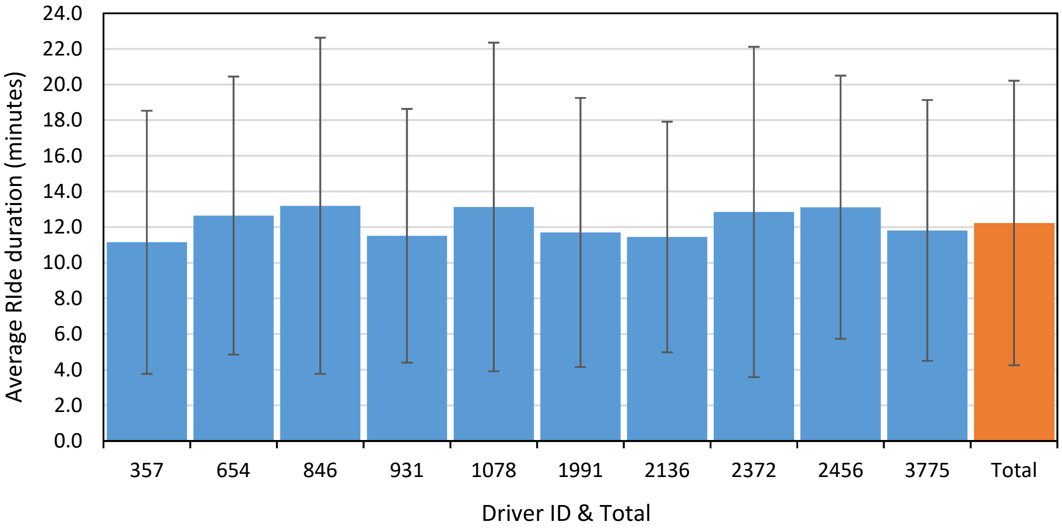


Figure 4.3 Average passenger ride (O-D) duration

4.2 Ride-hailing Efficiency Rate

This section presents the results of the ride-hailing efficiency rate as range values in terms of both times and mileages. However, before the results, one of the most important criteria about the determination of deadheading that was not explained in the methodology chapter is described in this section firstly. Since the RideAustin dataset does not indicate when the app is active, it is not known that when drivers are actively seeking rides. For that reason, distinguish between deadheading in-between two rides and commuting are crucial to measuring the efficiency rate. As it is mentioned in the methodology part, commuting segments were not considered in the scope of this study. In calculating, cases where drivers spent more than 1 hour between a drop-off and a pick-up were considered as shifts. In other words, if the empty duration between the previous ride end and next ride start is more than 1 hour, it is taken as commuting at the end of shift. This can be also considered as pre-shift for the next ride. It is assumed that drivers are likely still seeking rides with the RideAustin app on for less than 1 hour between rides. Contrary to Komanduri et al.`s (2018) research, which they assumed as 30 minutes, this assumption may not be a conservative estimate and could result in longer deadheading times in between rides. However, when the cumulative distribution of empty durations and corresponding average empty trip distance is taken into consideration for ten drivers, it seems to be a logical assumption.

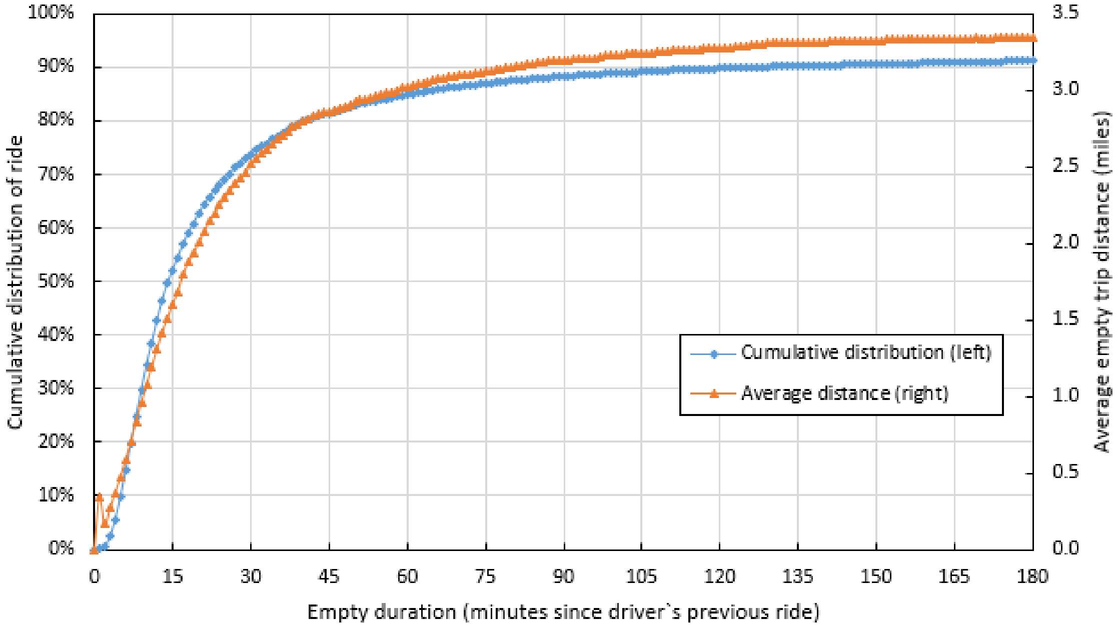


Figure 4.4 Cumulative distribution of rides and average empty trip distance between rides, by time since driver’s previous ride, adapted from Wenzel et al., (2019).

As it is shown in Figure 4.4, more than half of all rides (52%) were started within 15 minutes of the end of the previous ride of the drivers, while approximately another 30% of rides were started between 15 and 45 minutes after the end of a driver's previous ride. Considering the 60 minutes period after the drivers' previous rides end, it is seen that nearly 85 per cent of all trips were started within this time period. This means that approximately 15 per cent of empty trips were taken as commuting in this study. Figure 4.5 also demonstrates that until about 30 minutes after the previous ride, the average empty trips distance between rides increases sharply for each minute since the end of the previous ride. After that time, the average empty trip distance that is deadhead miles between rides continues to rise with a much slower rate. After 60 minutes, increasing empty duration between rides does not lead to a remarkable change in average empty trip distance and it remains almost constant just under 3.3 miles. Overall, this increase on empty trips distance indicates that most RideAustin drivers do not prefer to park their vehicles while waiting for the next ride request, but rather they are cruising around in this period.

Based on the 60 minutes limit in between rides, the drivers shift detail and number of rides per shift are summarised Table 4.2. The results in Table 4.2 shows that drivers had at least one break, which is longer than 1 hour, during one working day, the average shift per working day is nearly 2,4. Considering the number of rides per shift, the average value for 10 drivers is 6,6 rides. It is slightly higher than Henao's (2017) research, which equals to 6.4 based on 416 trips over the 65 shifts. However, it varies from 5,5 to 9,4 for individual driver level.

Table 4.2 Drivers shift details for less than 1-hour empty duration

Driver ID	**Rides**	**Empty Trips**	**Shifts**	**Working Days**	**Shift per Working Day**	**Rides per Shift**
357	1,232	1,036	196	78	2.51	6.29
654	1,174	988	186	78	2.38	6.31
846	1,085	970	115	62	1.85	9.43
931	1,098	950	148	74	2.00	7.42
1078	1,220	951	269	88	3.06	4.54
1991	1,636	1,435	201	87	2.31	8.14
2136	1,150	987	163	86	1.90	7.06
2372	1,296	1,065	231	85	2.72	5.61
2456	1,069	875	194	78	2.49	5.51
3775	1,129	1,001	128	56	2.29	8.82
Total	12,089	10,258	1,831	772	2.37	6.60

According to Wenzel et al. (2019), any travel started more than 60 minutes after the previous ride end includes at least some personal travel such as dropping off a child from school or running errands. However, Nair et al. (n.d.) indicated that ride-hailing drivers could wait for the new request more than an hour in small towns, based on anecdotal evidence from drivers' forum. As Komanduri et al. (2018) stated, the upper limit for wait times of drivers between rides can be easily redefined in case of industry standards provide a more accurate indication based on observations. The distribution of the number of empty trips that is more than 1 hour between rides is given in Figure 4.5 according to time intervals, excluding 63 trips that are more than 24 hours. As it is seen from Figure 4.5, there is a massive difference in the number of empty trips between 1 hour and 2 hours, but it is assumed that this is not a logical assumption for the upper limit of driver waiting time. Nevertheless, the ride-hailing efficiency rate was also measured by considering less than 2 hours empty durations to make a comparison (see Appendix E).

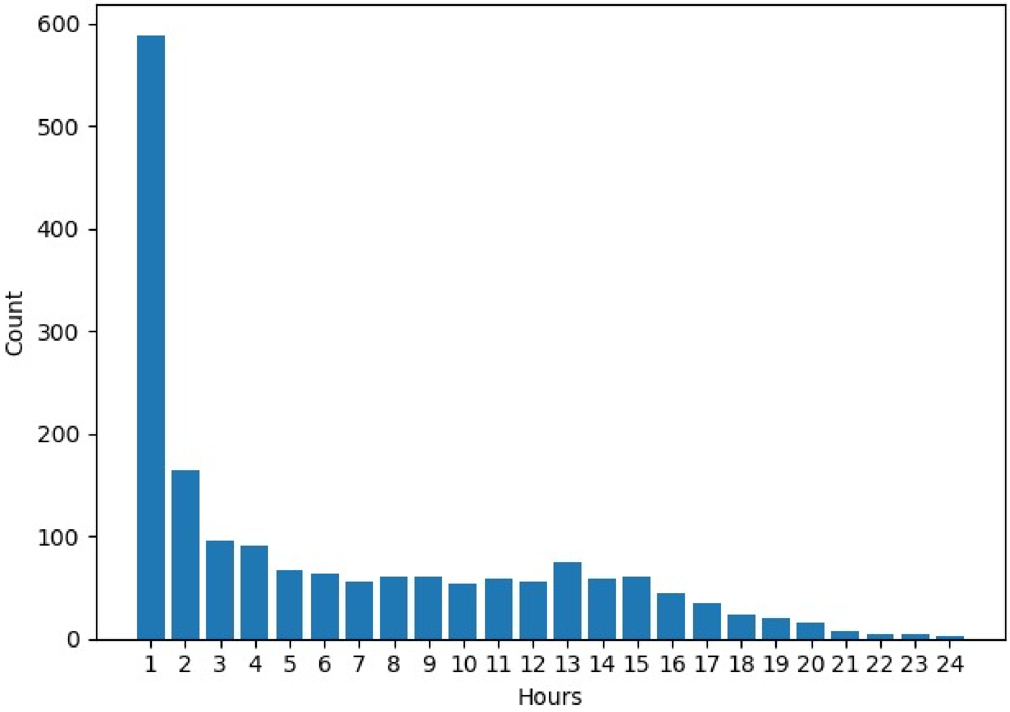


Figure 4.5 Number of empty trips for empty duration more than 1 hour between rides.

4.2.1 Efficiency in terms of Vehicle Miles Travelled (VMT)

Kontou et al. (2019) highlighted that there are four options that drivers can do after the passengers are dropped off at their destinations in case they are still active in service. These options can be categorised into two groups for this study; conservative vehicle miles travelled, and maximum vehicle miles travelled cases. For the conservative case; parking in a close-by location and waiting for a next trip request or accepting the new request and travelling to pick up the next passenger. While for the maximum VMT case; cruising around until dispatching another request or travelling to a high-demand location such as the central business district or airport.

The mileage ride-hailing efficiency rates were determined by the ratio of vehicle miles travelled with passengers to total vehicle miles travelled. Based on the assumptions, the analysis results are summarised in Table 4.3 according to both two scenarios.

Table 4.3 Efficiency of ride-hailing service in terms of vehicle miles travelled (VMT)

Driver ID	PMT	UVMT	Additional UVMT	Minimum VMT	Maximum VMT	PMT/ Max VMT	PMT/ Min VMT
	(miles)					(%)	
357	5,410.07	2,666.63	3,119.37	8,076.70	11,196.06	48.32	66.98
654	5,433.70	2,668.98	2,241.99	8,102.68	10,344.67	52.53	67.06
846	5,658.74	2,924.46	2,498.02	8,583.19	11,081.21	51.07	65.93
931	5,812.53	3,116.38	2,322.19	8,928.91	11,251.10	51.66	65.10
1078	7,577.35	3,359.84	3,066.20	10,937.19	14,003.39	54.11	69.28
1991	7,375.86	3,405.26	3,696.94	10,781.12	14,478.07	50.95	68.41
2136	6,247.80	3,717.46	3,093.77	9,965.26	13,059.03	47.84	62.70
2372	6,318.90	2,858.46	2,213.92	9,177.37	11,391.29	55.47	68.85
2456	5,906.79	3,351.30	1,963.98	9,258.09	11,222.08	52.64	63.80
3775	5,231.39	2,940.88	2,548.51	8,172.27	10,720.78	48.80	64.01
Total	60,973.12	31,009.67	26,764.90	91,982.79	118,747.69	51.35	66.29

Table 4.3 indicates that RideAustin efficiency rate is ranging between 51 % and 66%, considering the 10 drivers who have the highest trip number between 31 December 2016 and 31 March 2017. To better understanding, the efficiency of ride-hailing services and their impacts on VMT, the results in the table can be indicated as an extra mile version. This means that for every 100 miles with a passenger, a ride-hailing driver travels an additional 51 miles with empty seats for conservative scenario case, while 95 miles for the maximum travelling case. If deadhead miles generated by commuting segments are taken into consideration, results of the additional empty mile would be higher. Considered to individual driver level, mileage efficiency for conservative case varies from 62.70 per cent to 69.28 per cent, while for maximum miles travelled scenario, which is travelling without parking, differs between 47.74 per cent and 55.47 per cent. Since this study based on the assumptions, the actual efficiency of RideAustin service is in this range.

From the data in Table 4.3, it is seen that drivers belonging to identification numbers 1078 and 2372 are more efficient than the other drivers in both scenarios. This may reveal a correlation between the number of shifts per working day and mileage efficiency rate. According to the results in Table 4.2 and 4.3, it is seen that the ride-hailing efficiency ratio increases when the number of shifts per working day increases. Figure 4.6 display the average shift number per working day and percentage of ride-hailing efficiency for all ten drivers. However, this correlation can be caused by analysis method of this study since more than one-hour durations between rides were taken as commuting. As the commuting parts were not included in deadhead miles, the efficiency may find higher than actual.

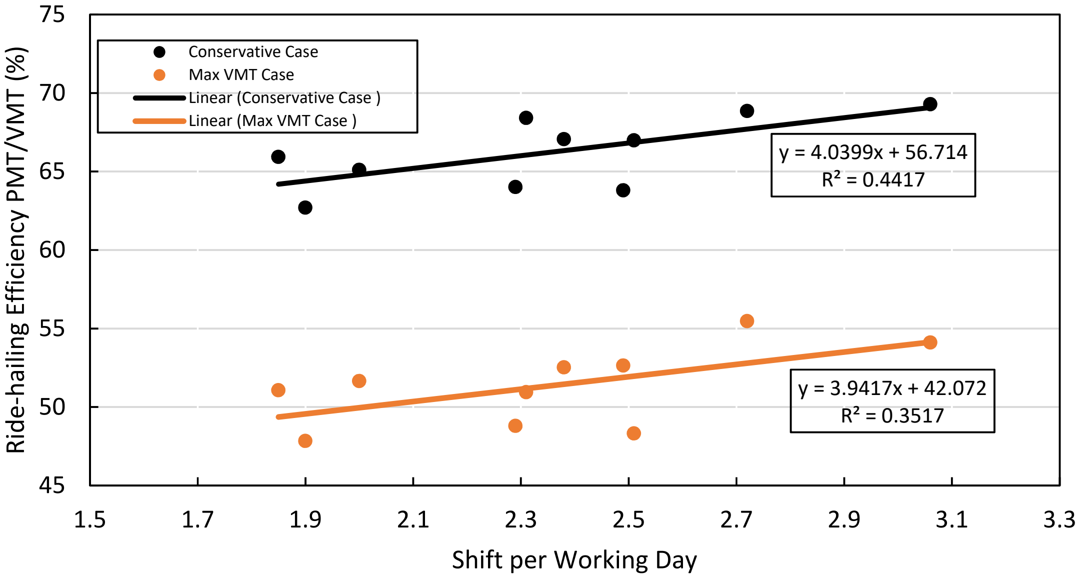


Figure 4.6 Average shift per working day and mileage ride-hailing efficiency

Previous to this study, seven studies present findings on the impacts of ride-hailing services on transportation efficiency in terms of vehicle miles travelled, based on the measured driver activity in different cities of the U.S., as of the August of 2019. Although, some of them has already indicated in the literature part, in this section previous findings are inspected only for made a comparison between findings of efficiency and deadheading rate.

The first study was carried out by Cramer and Krueger (2016) to compare the capacity utilisation rate, which is also known as efficiency, between ride-hailing and taxi services in two large cities; Los Angeles and Seattle. They revealed that the utilisation rate of Uber is 55.2 per cent for Seattle and 64.2 per cent for Los Angles. These results provided by Uber and they are based on the analysis on randomly selected 2,000 UberX drivers in both cities for the 12 months periods from 1 December 2014 to 1 December 2015. The main limitation of Cramer and Krueger's study is that it is not known whether the analysed sample size is representative of Uber driver activity. This is because the authors did not independently verify the findings. In addition to this, since the data of this study include only for when the Uber app was on, the commuting distance at the end of shifts was not taken into consideration (Henao on Marshall 2018).

Another study conducted by The San Francisco County Transportation Authority (SFCTA) finds that empty vehicle miles travelled that is non-revenue miles rate is about 20% for intra-city trips in San Francisco (SFCTA, 2017). This result based on the analysis of Uber and Lyft APIs data that provide approximate vehicle locations at five-second intervals, estimated passenger pick-up times, and active vehicle time on the app over the six weeks from mid-November to mid- December 2016. The limitation of this report is that they incorrectly calculated the efficiency rate of ride-hailing because over-heading segments of deadheading included in passenger O-D rides part, this causes overestimation in the result. In other words, empty distances from ride request to passenger pick-up locations were taken as passenger ride rather than empty miles. Apart from that, data include approximate pick-up and drop-off locations, rather than exact. Moreover, their method excludes the trips that begin and end outside the city core of San Francisco.

A recent study in Denver reveals that the conservative deadheading percentage of ride-hailing service is around 41% that is comprised of 25 % from cruising and over-heading segments and 15.8% from commuting at the end of the shifts (Henao and Marshall, 2018). This equates to 29.7 % in deadheading when excluding commuting part at the end of shifts. These findings based on 416 trips data that are directly collected from one of the authors who served as an Uber and Lyft driver over a period of 14 weeks during fall 2016. Contrary to other studies, this gave the author the opportunity to measure all deadheading segments. The main limitation of Henao and Marshall's research is that data size is relative to small and it is difficult to determine whether trip activity sample are representative of ride-hailing trips or not. Secondly, during collecting data author used two different ride-hailing services at the same time and he declined the ride requests, which are more than 15 miles far away from the driver's location, to minimise the empty VMT. Moreover, the author chose specific start locations and preferred to work during peak demand times of the day. As a consequence, this study provides a conservative representation of ride-hailing efficiency.

Recently, an online article published by Said (2018) demonstrates the analysis results of data that is obtained from Lyft for three different cities; New York, Chicago, and San Francisco. Although the way how the data was analysed and calculation methods are not clearly explained, one of the figures in the article provides sufficient information to measure ride-hailing efficiency rate. This is because it shows the average distance for cruising and over-heading part of deadheading, and passenger (O-D) ride. These results are also stated in Schaller's (2018) report. The research originally was carried out by Rocky Mountain Institute (RMI) and based on one-year trip data between 1 November 2016 and 31 October 2017. Given this data, it is measured that ride-hailing efficiency rates in New York, Chicago, and San Francisco were 59.3 %, 59.5%, and 69.2%, respectively.

Another recent study in California finds that deadhead miles are constituted close to 65 per cent of total trip miles, this equates to deadhead miles are approximately 40 per cent of total vehicle miles travelled. They used data that is obtained from both Uber and Lyft for the one-month period of October 2017 (George and Zafar, 2018). The limitation of this study, lack of any information about the size of data and whether the data are representative are not. Moreover, the report states that the result may be overestimated because most of the ride-hailing drivers use more than one apps at the same time. For instance, trip miles travelled on one ride-hailing platform may be recorded as deadhead miles on another. Apart from that, analysis results may include personal travel such as running personal errands because if the app is open, miles driven by drivers during these periods were recorded as deadheading VMT (George and Zafar, 2018).

A more recent study in Austin estimates that about 63 per cent of total RideAustin VMT is travelled with passengers, including commuting at the beginning and end of shifts (Komanduri et al., 2018). Considered to same periods of the current study (between January and March), the average efficiency rate is found around 64.2 per cent. The limitation of this study is that results were obtained by making assumptions on the RideAustin dataset because of uncertainty. Firstly, they assumed a uniform commute distance (two miles) and duration (five minutes) for the beginning and end of each shift. They also applied to the same assumption when the drivers spent more than 30 minutes between a drop-off and a pick-up. Moreover, in calculating the deadhead distance between rides, they accounted for straight-line distances rather than getting directions via APIs or adjusting for the real street network distance like Wenzel et al. (2019). Therefore, the findings of this study represent the lower end of the actual deadhead distances since the straight-line distance is the smallest measure of deadheading distance.

Lastly, similar to Komanduri et al.`s (2018) study, Wenzel et al. (2019) used to RideAustin dataset to estimate that about 45% of all ride-hailing VMT are deadhead miles, corresponding 26% from in between rides and 19% from commuting at the beginning and end of shift. They also estimated that drivers travelled 55 per cent more miles between ride requests within 60 minutes of each other, relative to the distance of passenger (O-D) rides. This indicates that when the commuting parts are excluded, the efficiency of the ride-hailing rate is measured as 64.5 per cent for rides less than 60 minutes empty duration. Similarly, the limitation of this study is caused by making assumptions for the data analysis part. Contrary to Komanduri et al. (2018), this study measured the commuting deadhead distance based on the assumption of drivers` residence location was estimated by computing the spatial median of first pick-up locations of all shifts for each driver. Moreover, they applied the adjustment factor that is 1.4 on measured straight-line distances between locations to represent the street network distance. Authors found this correlation by making a comparison between GPS-measured passenger rides distance and straight-line distances.

Table 4.4 Efficiency rate of ride-hailing services, excluding commuting segments

	Efficiency PMT/VMT (%)	**Deadhead miles per 100 "vehicle miles travelled with a passenger"**	**Source**
Austin	64.5	55.0	Wenzel et al. (2019)
Denver	70.3	42.2	Henao and Marshall (2018)
Chicago	59.5	68.1	RMI (2018)**
New York	59.3	68.6	
California	60.7	64.7	George and Zafar (2018)
San Francisco	80.0*	25.0*	SFCTA (2017)
	67.2	48.8	RMI (2018)**
Los Angles	64.2	55.8	Cramer and Krueger (2016)
Seattle	55.2	81.2	
This study (Austin)	66.3	50.8	Conservative case (1hr)
	51.4	94.6	Worst-case scenario (1hr)

*Efficiency was overestimated since the over-heading part was included to passenger (O-D) ride

**Source: https://www.sfchronicle.com/business/article/Lyft-trips-in-San-Francisco-more-efficient-than-12476962.php

In summary, the ride-hailing efficiency rate results of previous research and current study are stated in Table 4.4. The efficiency results in the table were measured by excluding the commuting segments of deadheading for the sake of comparison between studies. The findings in Table 4.4 suggest that deadhead miles for the ride-hailing services in the U.S. are varying depending on the local context. However, it should not be noted that the data size and collected periods are different between studies. In addition, as the matching algorithms of these services have been developed and the number of drives is increasing day by day, efficiency rates may not reflect the current situation of companies.

Overall, the findings of this study on efficiency rate limits are consistent with previous results, as shown in Figure 4.7. It is observed that the efficiency of ride-hailing services is mostly within the estimated range, except Denver and San Francisco cases. The upper limit represents the conservative case scenario, while the lower limit is considered as a worst-case scenario.

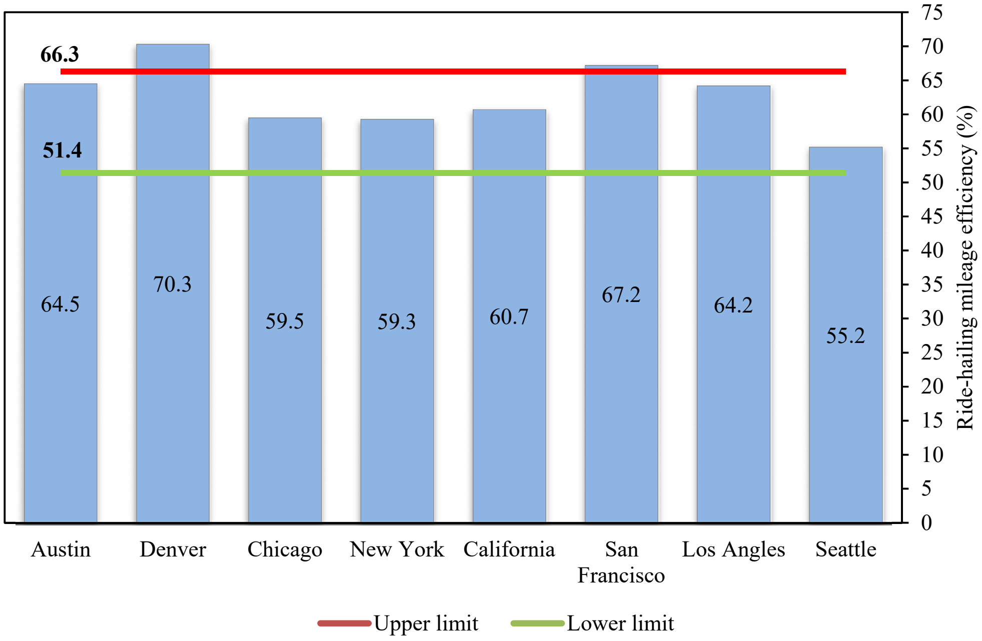


Figure 4.7 Efficiency rate of ride-hailing services from literature and the current study

4.2.2 Efficiency in terms of Vehicle Hours Travelled (VHT)

The ride-hailing efficiency rates in terms of times were determined by the ratio of vehicle hours travelled with passengers to total vehicle hours travelled. Based on the assumptions, the analysis results are summarised in Table 4.5 according to both two scenarios. Vehicle hours travelled, which is represented by PHT in this study, are measured to time differences between when the rides started, and the rides were completed. Empty trip duration, which was measured by means of Google APIs, are represented as unoccupied vehicle hours travelled, while empty duration represents the total time from previous rides end to next rides start. This term is commonly used as a deadheading time in literature.

Table 4.3 indicates that RideAustin efficiency rate is ranging between 47 % and 64%, considering the 10 drivers who have the highest trip number between 31 December 2016 and 31 March 2017. Considered to individual driver level, times efficiency for conservative case varies from 59.0 per cent to 68.5 per cent, while for total empty duration is taken into consideration, which is the actual time differences between rides, differs between 43.0 per cent and 51.9 per cent.

Table 4.5 Efficiency of ride-hailing service in terms of vehicle hours travelled (VHT)

Driver ID	**PHT**	**UVHT (Google Maps)**	**Empty Duration**	**Maximum VHT**	**Minimum VHT**	**PHT/ Max VHT**	**PHT/ Min VHT**
	(minutes)					**(%)**	
357	13,739.32	7,871.47	17,285.28	31,024.60	21,610.78	44.29	63.58
654	14,849.78	7,486.87	15,289.87	30,139.65	22,336.65	49.27	66.48
846	14,316.85	7,700.32	15,455.30	29,772.15	22,017.17	48.09	65.03
931	12,641.97	7,930.45	14,701.62	27,343.58	20,572.42	46.23	61.45
1078	16,003.88	7,856.70	15,865.00	31,868.88	23,860.58	50.22	67.07
1991	19,146.67	9,876.10	21,482.15	40,628.82	29,022.77	47.13	65.97
2136	13,171.80	9,149.57	17,448.23	30,620.03	22,321.37	43.02	59.01
2372	16,650.75	7,646.43	15,410.60	32,061.35	24,297.18	51.93	68.53
2456	14,023.92	7,984.40	14,257.97	28,281.88	22,008.32	49.59	63.72
3775	13,340.12	7,975.37	15,882.03	29,222.15	21,315.48	45.65	62.58
Total	147,885.05	81,477.67	163,078.05	310,963.10	229,362.72	47.56	64.48

It should be noted that although the time efficiency of ride-hailing service for the conservative case seems insignificant because actual time differences are known to measure the rate of deadheading times, it is not known whether drivers travelled along the all empty period. For that reason, the conservative case represents the situation where all next rides are dispatched to drivers just after or during the previous ride. In that case, drivers must travel with a time of measured duration of UVHT. This is crucial for calculation of fare productivity.

Previous to this study, only three studies present the results of ride-hailing services efficiency in terms of times, as shown in Table 4.6. The first study was carried out by Cramer and Krueger (2016) to compare the capacity utilisation rates between ride-hailing and taxi services in five large cities; Boston, Los Angeles, New York, San Francisco and Seattle. The study found that the time efficiency rate of UberX, based on the time that fare-paying passengers are in the car and total time that drivers active in-app, are varying between 43.6 per cent and 54.3 per cent according to cities. This indicates that drivers spent more time without passengers than with one in the car, during their shift hours for Seattle and Boston. The results of this study were based on the data that: the average of three days (January 9, April 11 and, July 13) in 2015 for Boston; periods from July to October 2015 for San Francisco; periods from 1 December 2014 to 1 December 2015 for other cities. The limitation of this study is that since results were provided by Uber it is not clear the data size and whether it is representative or not.

The second study is conducted by Henao (2017) in Denver and he measured to that about 41 per cent of driver working hours, excluding commuting at the end shift, was deadhead times. Data size and travel details are the same as those of Henao and Marshall (2018). Lastly, Komanduri et al. (2018) estimated also deadheading times of RideAustin based on the assumptions on datasets that were explained above. Considered to same periods of current study, average efficiency rate in terms of time is found around 49 per cent, including the commuting parts of deadheading.

Table 4.6 Ride-hailing efficiency rate in terms of vehicle hours travelled, excluding commuting segments

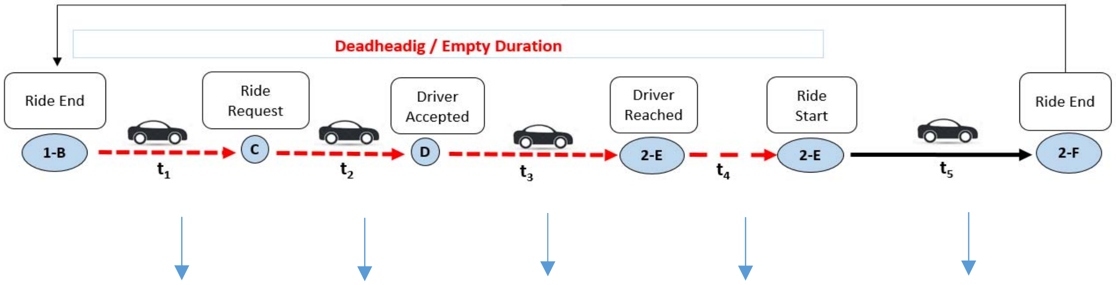
	Efficiency PHT/VHT (%)	**Source**
Boston	46.1	
Los Angles	50.3	
New York	51.2	Cramer and Krueger (2016)
San Francisco	54.3	
Seattle	43.6	
Denver	41.3	Henao (2017)
Austin	48.9*	Komanduri et al. (2018)
This study	64.5	Conservative case (1hr)
	47.6	Worst-case scenario (1hr)

*This efficiency rate includes the commuting parts of deadheading

Overall, the result of the current study is consistent with previous studies, as shown in Table 4.6. It should be noted that the efficiency rate of ride-hailing services in terms of times is generally lower than miles-based measured. Across the results, for example, for mileage-based efficiency of ride-hailing service in Denver was founded as 70.3 per cent by excluding commuting part, while time-based efficiency was measured as 41.3 per cent. This difference can be caused by many factors such as, arriving early to the passenger pick-up location and waiting for them, parking or driving more slowly between drop-off passenger and new ride request or taking a break during their shifts that are counted as work hours (Cramer and Krueger, 2016).

In addition to the efficiency rate, a statistical summary of the duration of each segment in the driver activity are stated in Table 4.7. The average waiting time of riders for RideAustin service is almost 4 minutes. Also, riders wait for an additional nearly one and a half minutes at their pick-up location before the ride starts. However, during this period drivers may wait for a passenger in such a case putting suitcases in the trunk of the car. Considered to average ride durations, drivers spent approximately 44 % more time than trip duration for carrying passengers after the ride request.

Table 4.7 Average duration of deadheading segments and passenger rides



Unit (hh:mm:ss)	Waiting or Cruising for a ride	Passenger Waiting Time		Driver Waiting Time	Passenger Ride (O-D)
		Driver Response	Over-heading		
Mean	00:10:42	00:00:09	00:03:50	00:01:22	00:12:14
SD	00:11:46	00:00:11	00:02:50	00:01:50	00:07:59
Median	00:06:26	00:00:04	00:03:14	00:00:44	00:10:29
Total	1828:12:54	30:44:47	687:34:50	276:29:59	2464:45:03

4.3 Fare Productivity

This section focuses on the fare productivity of RideAustin services based on the fare paid by passengers. Since RideAustin is a non-profit ride-hailing company, driver earnings per trips should be higher than the other services that receive about 25 per cent commissions. However, gross earnings of drivers were not measured in this study because parameters that determine the fare amount fluctuated along the analysis period. In other words, RideAustin service has changed its policy on determining fares and fees in order to obtain an optimum level for gross margin per trip (Tryba and Goldenberg, 2017). For this reason, estimated drivers' gross earnings in this study include the RideAustin service fee. Based on the RideAustin dataset, fare per corresponding parameters such as a working day or ride minutes are summarised in Table 4.8.

Table 4.8 RideAustin fare statistic summary

Driver ID	Total Fare ($)	Fare per working day	Fare per Ride	Fare per Ride Mile	Fare per Ride Minute	Fare per Minute	Fare per Min. Mile	Fare per Max. Mile
357	$15,004.08	£192.36	$12.18	$2.77	$1.09	$0.48	$1.86	$1.34
654	$14,103.59	£180.82	$12.01	$2.60	$0.95	$0.47	$1.74	$1.36
846	$15,421.80	£248.74	$14.21	$2.73	$1.08	$0.52	$1.80	$1.39
931	$16,737.91	£226.19	$15.24	$2.88	$1.32	$0.61	$1.87	$1.49
1078	$17,877.00	£203.15	$14.65	$2.36	$1.12	$0.56	$1.63	$1.28
1991	$19,026.25	£218.69	$11.63	$2.58	$0.99	$0.47	$1.76	$1.31
2136	$14,643.71	£170.28	$12.73	$2.34	$1.11	$0.48	$1.47	$1.12
2372	$20,244.67	£238.17	$15.62	$3.20	$1.22	$0.63	$2.21	$1.78
2456	$14,068.81	£180.37	$13.16	$2.38	$1.00	$0.50	$1.52	$1.25
3775	$14,918.71	£266.41	$13.21	$2.85	$1.12	$0.51	$1.83	$1.39
Total	$162,046.53	£209.90	$13.40	$2.66	$1.10	$0.52	$1.76	$1.36

The findings indicate that gross earning of RideAustin drivers is around $210 per working day, including RideAustin`s service fee and drivers` expenses such as gas and car depreciation. When considering the total collecting fare per working day for individual driver level, it is varying between $180 and $265. The main reason for these significant differences between drivers is having different average trips number per working day. In other words, as the number of trips increases, gross earnings of drivers per working day rise. The average fare of 12,089 rides was found $13.40 and this is consistent with Henao`s (2017) result based on 416 rides (including both Uber and Lyft) in Denver. The average passenger cost of trips is found as $13.07, including Uber and Lyft commissions.

The analysis of driver's data shows that the average fare per ride mile is $2.66, while per ride minute is $1.10. Considering the individual driver level, fare per ride mile are ranging from $2.34 to $3.20, while per minute are varying between $0.95 and $1.22. However, it should not be overlooked that the surge factor, which depends on the ride demand, and traffic conditions significantly affect the fares. Apart from that, driver working days and time of day can be another reason for these differences between drivers.

When the ratio between average gross revenue per trip ($15.14) and cost of revenue per trip ($11.66 for driver earnings) are taken into consideration based on findings of Tryba and Goldenberg (2017), it is found that driver gross earning per trip is approximately 77 per cent of total trip fare. This shows that RideAustin takes an average 23 per cent of total fare as a service fee. Considered to the time and distance drivers spent with a passenger, RideAustin driver would be making roughly $65 per hour and $2.66 per mile. However, taking account for the overall duration within the work shift, the average gross earnings of drivers reduced to $31.2 per hour. On the other hand, average gross earnings per miles for conservative case miles and worst-case scenario are $1.76 and $1.36, respectively. If the average 23 per cent service fee is charged, the drivers' gross earnings are found to be $24 per hour. Henao (2017) measured the gross earnings around $15.7 per hour after including all driver times.

A 2018 independent survey on ride-hailing drivers indicated that the median net earnings of UberX drivers are $14,73 per hour (including tips), based on 1.911 driver respondents (Ridester,2019). This survey was taken over 2 months from May to July of 2018 and collected 2,603 self-reported driver earnings declarations, including 719 screenshots of driver earnings from Uber or Lyft driver app (Ridester,2019). Another more recent study from Stanford University showed that the gross hourly earnings of all Uber drivers in the U.S. were $21.07 between January 2015 and March 2017, including Uber' service fee (Cook et al., 2019). However, as most of the ride-hailing drivers use more than one apps at the same time (e.g., using together Uber and Lyft), the actual gross earnings of drivers can be higher than estimated. Overall, these findings indicate that the gross earnings of RideAustin drivers can be higher than the market average.

CHAPTER V

CONCLUSION

5.1 Summary

The popularity of app-based on-demand ride services has exploded globally since the introduction of Uber in 2009. Most prior studies show that this disruptive innovation in the taxi business has changed the ways people travel in major cities and that these services are significantly competitive and interactive with other modes of transport (Tirachini and Gomez-Lobo, 2019; Henao and Marshall, 2018; Clewlow & Mishra, 2017; Rayle et al., 2016 and 2014). However, the rapid growth of ride-hailing services has raised many questions about their role in urban transport. The impacts of these new mobility services on urban transport systems in terms of VMT is one of the controversial issues to be answered. Moreover, considered to future with an emergence of self-driving vehicles, which is estimated to accelerate the usage of ride-hailing services, understanding the influence of these services on transportation become more crucial to shape future transportation systems. It is difficult to predict what will happen when the driverless vehicles are used to ride-hailing. However, without a clear understanding of how these services impacts on today`s transportation, it is hard to manage and shape future transportation systems.

Many authors have emphasised the importance of determining the effect of ride-hailing services on vehicle miles travelled and associated problems such as congestion and pollution (Rodier, 2018; Clewlow & Mishra, 2017; Henao, 2017; Rayle et al., 2016). Nonetheless, up to the present, there is scant evidence on this topic due to the lack of open data, especially in the UK. Within this framework, initially, the primary purpose of this research was to investigate the transportation efficiency of private hire vehicle (PHV) drivers across the UK by collecting data via surveys. However, after committee decision about data collection, the publicly-available database that is created by RideAustin, which is a non-profit ride-hailing company in Austin, was used to investigate the efficiency of ride-hailing services.

Contrary to previous studies, this study presents the findings related to the efficiency ratio as a range value based on lower and upper limits. It is assumed that actual efficiency is taken place between this range. The results presented here are based on 12,089 rides data, which are conducted by ten drivers who have the highest trip number from December 31, 2016, to March 31, 2017.

5.2 Key Findings

Based on analysis of RideAustin data within the scope of this research, the following results can be drawn:

- The efficiency of RideAustin services in terms of vehicle miles travelled are varying between 51.4% and 66.3%, excluding commuting segments of deadheading. This means that for every 100 miles with a passenger, a ride-hailing driver travels an additional 51 miles with empty seats for conservative scenario case, while 95 miles for the worst-case scenario. These indicate a significant amount of deadheading travel as a percentage of total travel. However, these findings show that drivers can increase their efficiency by up to 29 per cent if they park immediately after the previous ride ends, thereby saving fuel consumption of their vehicles.
- While considering times efficiency of ride-hailing services, RideAustin efficiency rate is ranging between 47,6 % and 64.5%. But, the actual estimated time efficiency of RideAustin is 47.6 per cent for rides less than 60 minutes between each other. This indicates that drivers spent more time without passengers than with one in the car, during their shift hours.
- Drivers started the more than half of their new rides within the 15 minutes that after their previous trip was completed. The average deadheading miles during this period increased steeply for each minute. This suggests that ride-hailing drivers are more active in seeking new rides for the first 15 minutes period.
- From the riders' point of view, the average waiting time for RideAustin services is almost 4 minutes, and drivers and passengers are waiting for additional nearly one and a half minutes at their pick-up location before the ride starts.
- Given the details of rides, more than half of riders use RideAustin services for travelling a short distance that is less than 4 miles. The average duration of trips is just over the 12 minutes, while the average trip length is 5.04 miles. This indicates that drivers spent approximately 44 % more time than trip duration for carrying passengers after the ride request.
- Drivers completed an average of 15.66 rides per working day and collected average $13.40 fare per rides, excluded tips. Based on average shifts per working day, drivers gave at least one break that is more than 60 minutes during worked days.

5.3 Conclusion

In conclusion, this dissertation provides insights into the efficiency of ride-hailing service based on capacity utilisation. The results presented in this dissertation indicate that ride-hailing services generate a high level of additional VMT in between two rides due to empty trips. Even in the conservative case scenario, it was measured that ride-hailing drivers have to travel with empty seats extra half of the ride miles for carrying passengers. Considered the whole activity scheme of the drivers, including commuting, a considerable amount of deadheading mileages is expected to add to the urban system. As a consequence of this, total empty VMT levels in urban networks are likely increasing with the increasing popularity of this new mobility service. This leads to rising concerns about their effects on congestion and associated vehicle emissions in the urban transportation network, especially for highly dense cities that have already congested streets.

Although ride-hailing services generate additional VMT due to deadheading, the social benefits of these services should not be overlooked. Considered customer perspectives, these services are providing faster, more reliable, cheaper transportation services than taxis. More importantly, ride-hailing are increasing the customers' mobility and reducing drunk drivers and resolving parking problems. This is crucial for cities with not having an effective public transit system because ride-hailing users are more likely to have substituted rides in personal vehicles.

Despite this study provides data for policymakers and transport planners who want to evaluate the impacts of ride-hailing services on regional congestions and associated environmental pollutions, the net effect of ride-hailing use on total VMT are challenging to assess. Without considering the travel behaviour of users, the judgement of these services cannot be fair. For that reason, more accurate results can be obtained by considering both the quantitative analysis on drivers’ activity and survey-based research on identifying the travel behaviour of users in the city, as in the research of Henao (2017). For example, the answer to the question of how ride-hailing customers might have travelled if these services did not exist is essential to understand the modal substitution and trip generation effects. Moreover, the occupancy rate of ride-hailing trips is the critical factor for determining the impacts on VMT. As a result, in addition to meaningful data provided commercial companies, comprehensive simultaneous surveys of riders are necessary to understand the overall impacts on the urban pattern.

5.4 Limitations and Recommendations

The findings of this study have to be seen in the light of some limitations. The main limitation is that the driver sample size relative to the overall number of drivers of RideAustin. Since committee decision brought about to change the research field of this study, analysis of all data in the dataset was not possible in a short time. For that reason, the chosen sample size may not be appropriate to represent of all RideAustin app-based on-demand ride service and results reported herein may not generalizable for all city. Thus, more comprehensive samples should be considered by new studies.

Secondly, the analysis methods of the data are based on assumptions that affect the results of the study. Limited information about driver activity in dataset led to assumptions to carry out the analysis. The main assumption of analysis is that more than 60 minutes between two consecutive rides were taken as commuting. This duration may be high for most drivers to wait for a new request. If industry standards provide a more accurate indication based on observations, the upper limit of passenger waiting time can be modified easily.

Moreover, empty trip distance and duration were measured by means of Google Distance Matrix API that provides a distance of the recommended route between two locations and corresponding estimated travel time based on the historical traffic conditions. This analysis method can be improved by considering the departure times of empty trips when querying the trip data. This provides more accurate results for empty trip duration and distance since traffic conditions are quite different between peak and off-peak periods in urban areas.

Another limitation caused by assumption is that the average speed of drivers in between rides was taken about 25 miles per hour for the calculation of additional UVMT, based on the passenger (O-D) rides. However, in real case drivers can travel more slowly during the empty period. For example, in Henao`s (2017) research, the average speed of passenger rides was roughly 29 mph, while the average speed of driver between the period from request to passenger pick-up was around 14 mph. Thus, it is probable that calculated maximum VMT are overestimated and represents the top limits for the worst-case scenario. The average speed for new research can be taken as a more reasonable value.

Lastly, commuting segment of deadheading at the beginning and end of each shift were not considered in the analysis. Including all segments of driver's pattern is extremely important from a transportation policy perspective to evaluate the actual efficiency of ride-hailing services in cities. For that reason, this study can be improved by considering commuting part based on the logical assumption such as Wenzel et al.` (2019) research.

5.5 Future Research

Using the RideAustin travel data set, many types of research can be followed with different perspectives on the effects of riding services on urban transport and their possible future impact. Two possible research topics are suggested below, but not in detail.

Pooling option of ride-hailing services, in other words, ride-sharing can be a possible way of reducing empty VMT and increasing ride-hailing efficiency. But, this might result in higher total VMT in the networks since pooled ride-hailing services such as UberPool offer lower price of a ride in return for longer and less reliable travel time. Comprehensive research is needed to reveal the net impacts of ride-sharing of ride-hailing services on VMT. Based on the dataset, similar O-D rides can be identified by investigating the travel patterns and considering the departure times ride-sharing scenarios can be investigated.

Looking forward with the fully autonomous ride-hailing future, right-size fleets that able to meets the customer demand would be an effective solution to obtain a more sustainable, safe and equitable transportation system. However, more research is needed to identify the net impacts on VMT and deadheading that is likely to occur under a fully autonomous ride-sharing future. Ride-Austin datasets can be used for quantifying the number of vehicles, fleets size and possible deadheading percentage.

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APPENDICES

APPENDIX A: SPATIAL ANALSIS DATA

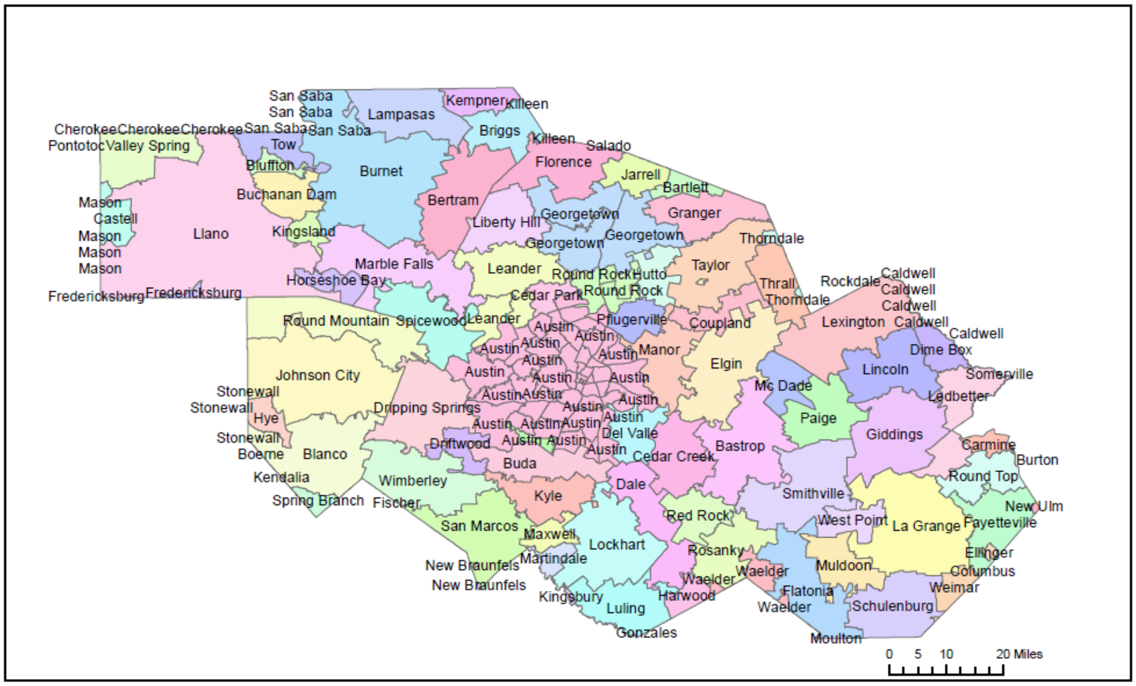

Figure A.1 Zip Code names and corresponding boundaries according to CAMPO

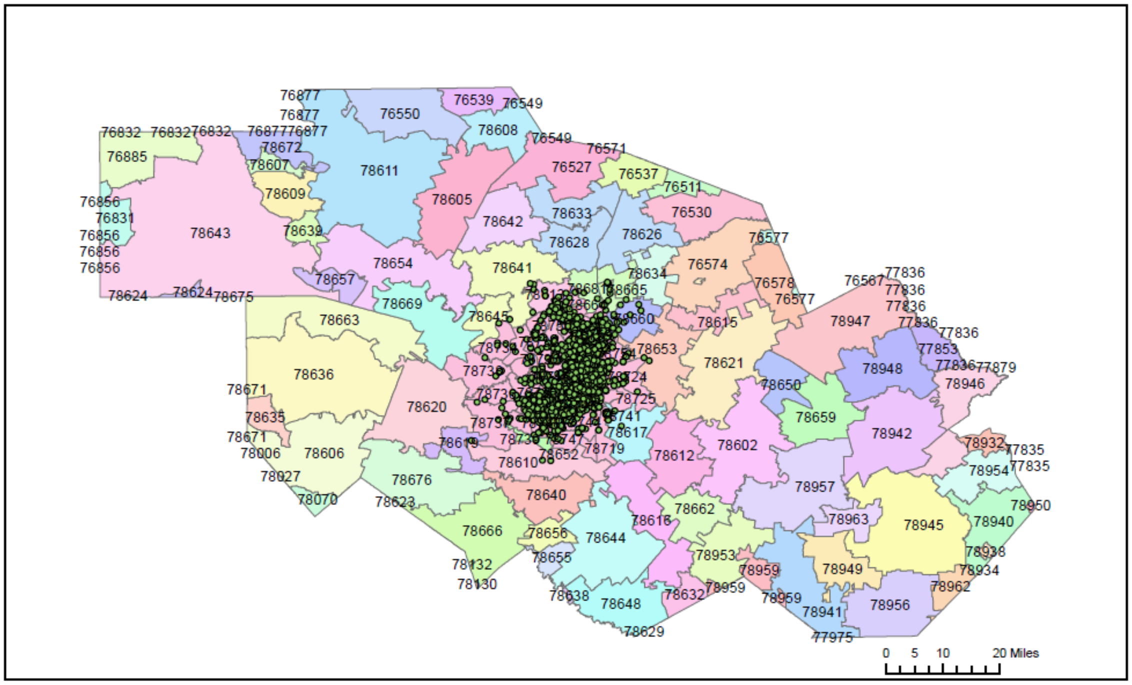

Figure A.2 Distribution of rides origins

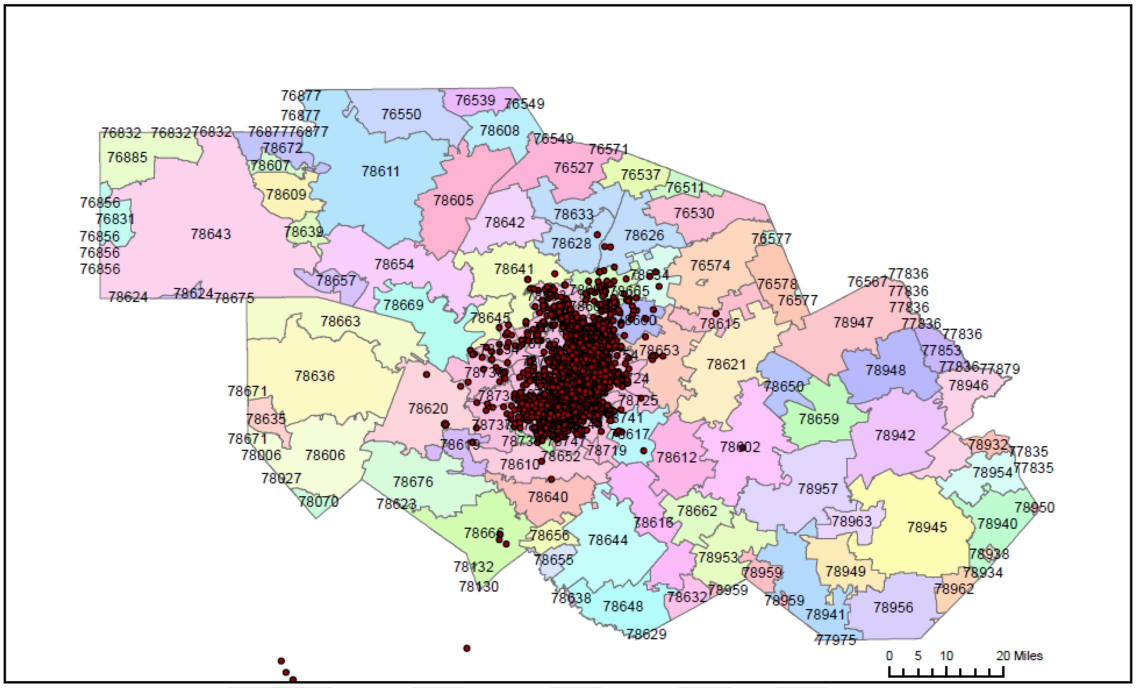

Figure A.3 Distribution of rides destinations

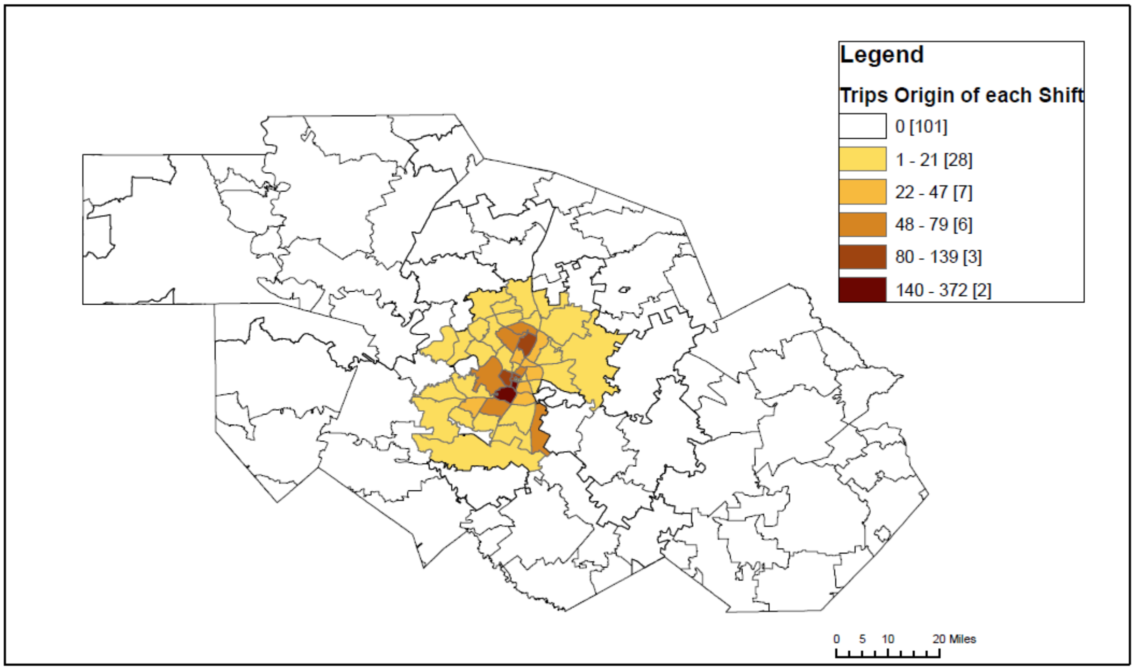

Figure A.4 Distribution of first rides origins of each shift

Zoning map of Austin was provided by the city of Austin open data portal.

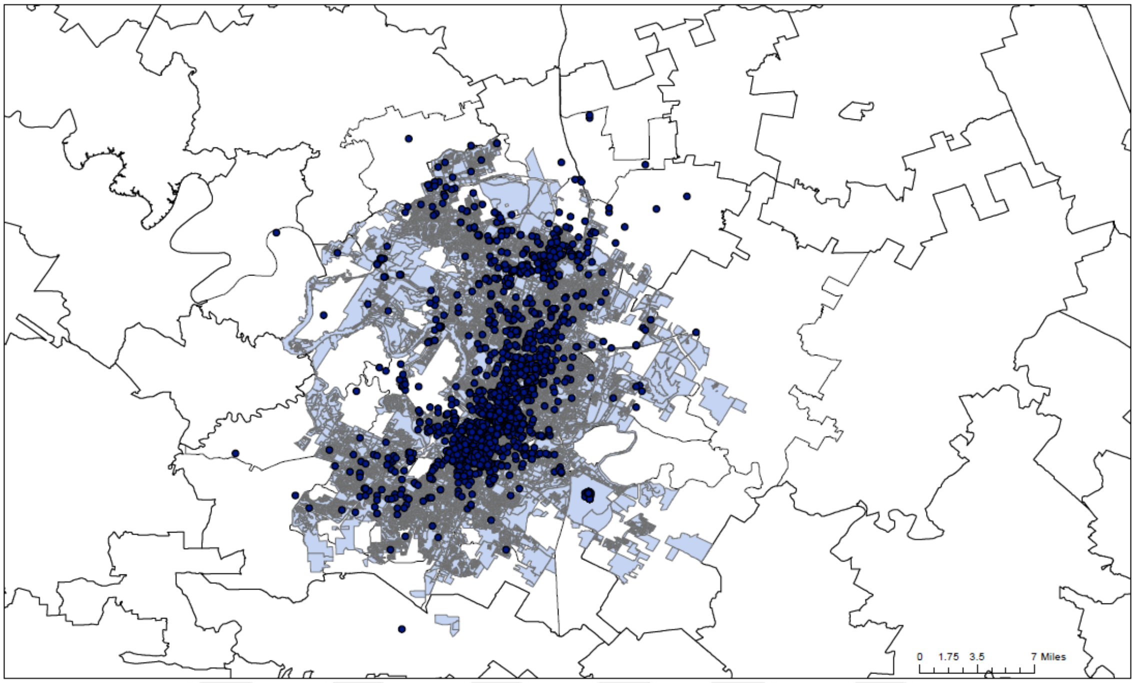

Figure A.5 Distribution of first rides origins of each shift in zoning maps

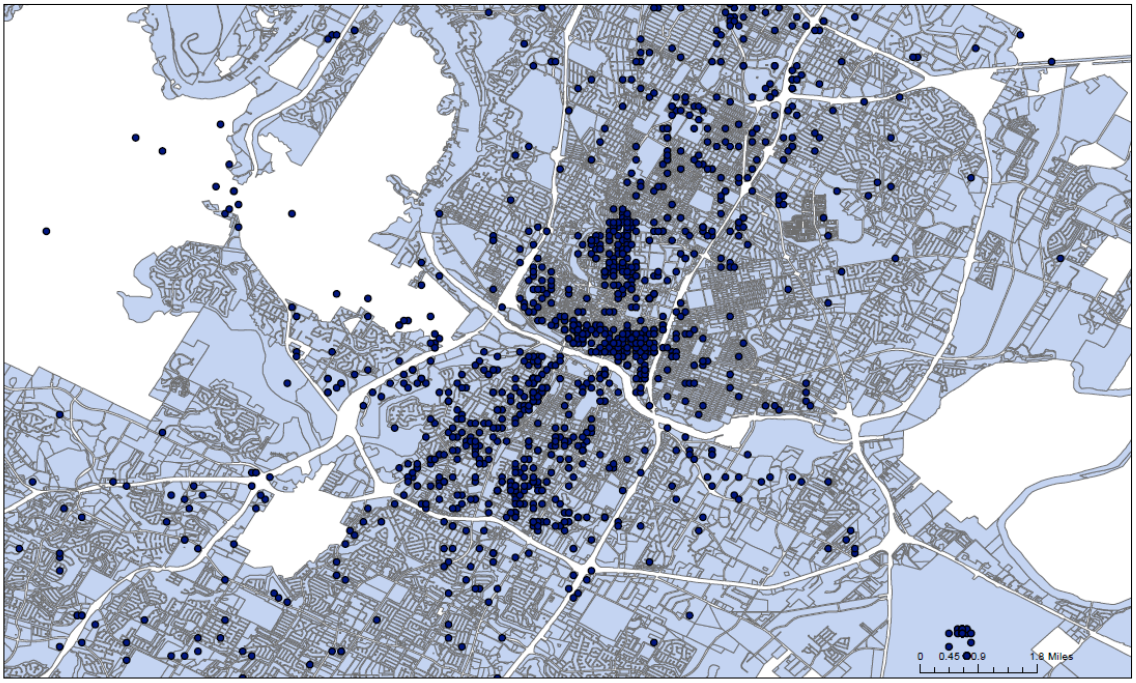

Figure A.6 Distribution of first rides origins of each shift in zoning maps, zoomed in.

APPENDIX B: ADDITIONAL UVMT CALCULATION

Table B.1 illustrates the analysis data and how additional UVMT distances are calculated. Since recorded ride distance and time at the ride start and ends are given in dataset, distance and duration of each individual trip can easily be calculated. Then average speed of trips was measured by using this information. The fourth column in the table represents the average speed of each driver in terms of mile per seconds. Time difference between empty trip distance and duration that are obtained by GoogleMap indicates the extra time for drivers between rides. Finally, additional UVMTs are measured by multiplying these times with average speed of drivers. These are indicated in the last column of table

Table B.1 Calculation of additional Unoccupied Vehicle Miles Travelled (UVMT) for less than 1-hour empty duration

Driver ID	Total Ride Distance (miles)	Total Ride Duration (sec)	Mile per second	Empty Trip Duration - UVHT (sec)	Additional UVMT (miles)
357	5,410.07	824,359	0.0066	475,313	3,119.37
654	5,433.70	890,987	0.0061	367,628	2,241.99
846	5,658.74	859,011	0.0066	379,206	2,498.02
931	5,812.53	758,518	0.0077	303,039	2,322.19
1078	7,577.35	960,233	0.0079	388,562	3,066.20
1991	7,375.86	1,148,800	0.0064	575,804	3,696.94
2136	6,247.80	790,308	0.0079	391,343	3,093.77
2372	6,318.90	999,045	0.0063	350,030	2,213.92
2456	5,906.79	841,435	0.0070	279,774	1,963.98
3775	5,231.39	800,407	0.0065	389,925	2,548.51
Total	60,973.12	8,873,103	0.0069	3,900,624	26,803.84

APPENDIX C: DATA ANALYSIS RESULT SUMMARY

Table C.1 Passenger O-D ride duration summary statistics

Driver ID	Total	Mean	Std. Dev.	Median
	(hh:mm:ss)			
357	228:59:19	00:11:09	00:07:23	00:09:22
654	247:29:47	00:12:39	00:07:48	00:10:45
846	238:36:51	00:13:12	00:09:26	00:11:00
931	210:41:58	00:11:31	00:07:07	00:09:58
1078	266:43:53	00:13:08	00:09:13	00:11:02
1991	319:06:40	00:11:42	00:07:33	00:10:11
2136	219:31:48	00:11:27	00:06:28	00:10:18
2372	277:30:45	00:12:51	00:09:16	00:10:57
2456	233:43:55	00:13:07	00:07:23	00:11:55
3775	222:20:07	00:11:49	00:07:19	00:10:00
Total	2464:45:03	00:12:14	00:07:59	00:10:29

Table C.2 Driver waiting time (time from driver reached on pick-up location to ride starts) summary statistics

Driver ID	Total	Mean	Std. Dev.	Median
	(hh:mm:ss)			
357	24:51:56	00:01:13	00:01:58	00:00:36
654	27:55:52	00:01:26	00:01:52	00:00:44
846	23:54:53	00:01:19	00:01:53	00:00:31
931	28:40:31	00:01:34	00:01:42	00:00:59
1078	25:32:16	00:01:15	00:01:33	00:00:42
1991	33:29:19	00:01:14	00:01:31	00:00:41
2136	29:36:17	00:01:33	00:02:16	00:00:48
2372	32:10:20	00:01:29	00:02:13	00:00:48
2456	26:50:40	00:01:30	00:01:36	00:00:55
3775	23:27:55	00:01:15	00:01:33	00:00:39
Total	276:29:59	00:01:22	00:01:50	00:00:44

Table C.3 Passenger waiting time (time from dispatched on to driver reached on pick-up location) summary statistics

Driver ID	Total	Mean	Std. Dev.	Median
	(hh:mm:ss)			
357	77:20:45	00:03:46	00:02:52	00:03:03
654	78:07:18	00:04:00	00:02:57	00:03:26
846	88:08:54	00:04:53	00:03:14	00:04:22
931	54:41:22	00:02:59	00:02:18	00:02:28
1078	84:17:55	00:04:09	00:03:04	00:03:29
1991	114:47:58	00:04:13	00:03:04	00:03:30
2136	85:29:13	00:04:28	00:02:46	00:03:59
2372	85:04:06	00:03:56	00:02:54	00:03:25
2456	73:10:21	00:04:06	00:02:34	00:03:36
3775	62:57:01	00:03:21	00:02:27	00:02:51
Total	804:04:53	00:04:00	00:02:53	00:03:23

Table C.4 Over-heading duration summary statistics

Driver ID	Total	Mean	Std. Dev.	Median
	(hh:mm:ss)			
357	74:13:43	00:03:37	00:02:49	00:02:55
654	75:31:51	00:03:52	00:02:53	00:03:18
846	85:45:51	00:04:45	00:03:10	00:04:13
931	51:41:48	00:02:49	00:02:15	00:02:19
1078	81:00:56	00:04:00	00:03:00	00:03:18
1991	110:50:05	00:04:04	00:03:01	00:03:23
2136	82:02:23	00:04:17	00:02:43	00:03:48
2372	81:50:52	00:03:47	00:02:51	00:03:18
2456	70:47:32	00:03:58	00:02:31	00:03:30
3775	59:35:40	00:03:10	00:02:24	00:02:39
Total	687:34:50	00:03:50	00:02:50	00:03:14

Table C.5 Driver response time (time from dispatch to driver accept) summary statistics

Driver ID	Total	Mean	Std. Dev.	Median
	(hh:mm:ss)			
357	03:07:37	00:00:09	00:00:10	00:00:05
654	02:35:27	00:00:08	00:00:11	00:00:03
846	02:23:03	00:00:08	00:00:10	00:00:03
931	02:59:34	00:00:10	00:00:11	00:00:04
1078	03:16:59	00:00:10	00:00:13	00:00:04
1991	03:57:53	00:00:09	00:00:11	00:00:04
2136	03:26:50	00:00:11	00:00:13	00:00:05
2372	03:13:14	00:00:09	00:00:10	00:00:05
2456	02:22:49	00:00:08	00:00:10	00:00:03
3775	03:21:21	00:00:11	00:00:11	00:00:06
Total	30:44:47	00:00:09	00:00:11	00:00:04

Table C.6 Waiting or cruising for a ride time (time from rides ends to dispatch) summary statistics for less than 1-hour empty duration

Driver ID	Number of Empty Rides	No Cruising for a ride	Total	Mean	Std. Dev.	Median
			(hh:mm:ss)			
357	1,036	11	207:43:05	00:12:02	00:12:21	00:07:54
654	988	24	168:26:54	00:10:14	00:12:19	00:05:12
846	970	17	159:53:20	00:09:53	00:11:31	00:05:22
931	950	18	173:43:25	00:10:58	00:11:24	00:07:11
1078	951	23	184:56:26	00:11:40	00:12:40	00:06:59
1991	1435	37	233:09:30	00:09:45	00:11:18	00:05:17
2136	987	34	193:57:21	00:15:42	00:12:06	00:07:34
2372	1065	35	161:22:19	00:13:02	00:11:05	00:04:45
2456	875	19	155:05:16	00:14:07	00:11:35	00:06:40
3775	1001	9	189:55:18	00:13:54	00:11:06	00:07:52
Total	10,258	227	1828:12:54	00:10:42	00:11:46	00:06:26

Table C.7 Times Ride-hailing efficiency summary for less than 1-hour empty duration

Driver ID	PHT	UVHT (Google Maps)	Empty Duration	Maximum VHT	Minimum VHT	PHT/ Max VHT	PHT/ Min VHT
			(hh:mm:ss)			(%)	
357	228:59:19	131:11:28	288:05:17	517:04:36	360:10:47	44.29	63.58
654	247:29:47	124:46:52	254:49:52	502:19:39	372:16:39	49.27	66.48
846	238:36:51	128:20:19	257:35:18	496:12:09	366:57:10	48.09	65.03
931	210:41:58	132:10:27	245:01:37	455:43:35	342:52:25	46.23	61.45
1078	266:43:53	130:56:42	264:25:00	531:08:53	397:40:35	50.22	67.07
1991	319:06:40	164:36:06	358:02:09	677:08:49	483:42:46	47.13	65.97
2136	219:31:48	152:29:34	290:48:14	510:20:02	372:01:22	43.02	59.01
2372	277:30:45	127:26:26	256:50:36	534:21:21	404:57:11	51.93	68.53
2456	233:43:55	133:04:24	237:37:58	471:21:53	366:48:19	49.59	63.72
3775	222:20:07	132:55:22	264:42:02	487:02:09	355:15:29	45.65	62.58
Total	2464:45:03	1357:57:40	2717:58:03	5182:43:06	3822:42:43	47.56	64.48

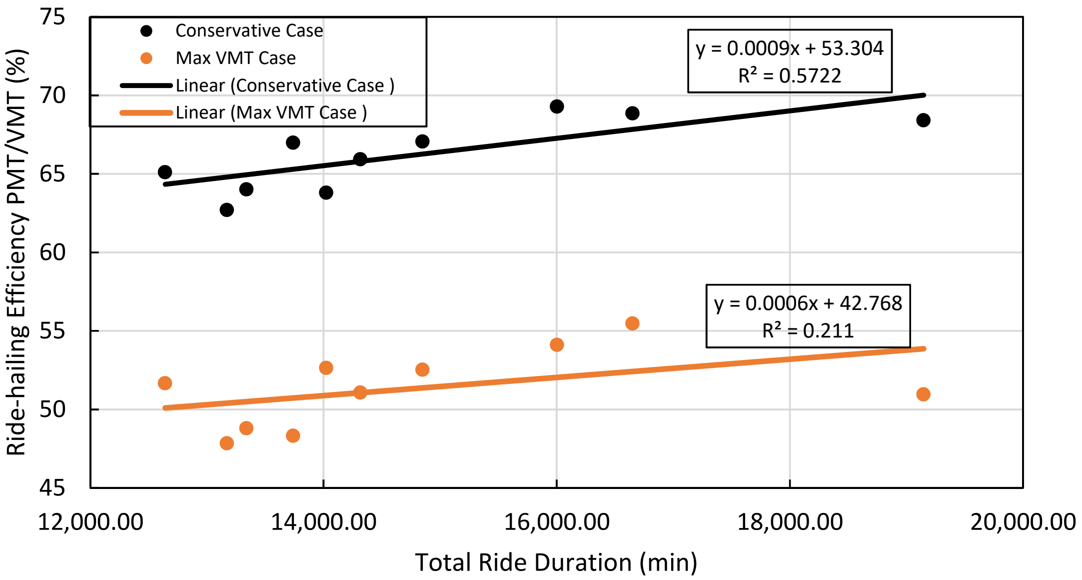

Figure C.1 Total ride duration and mileage ride-hailing efficiency

Figure C.1 displays the total time of driver travelled passengers and ride-hailing efficiency rate according to drivers. This figure suggests that as the passenger ride duration increases, the efficiency of the driver in terms of vehicle miles travelled increase, as well

APPENDIX D: DATA ANALYSIS RESULT SUMMARY, INCLUDED GPS-MEASURED DISTANCES OF OVERHEADING

Table D.1 Empty Trip distance (UVMT) summary statistics according to drivers for less than 1-hour empty duration

Driver ID	Empty Trips	Total Distance	Mean	Std. Dev.	Median
		(miles)			
357	1,036	2,666.63	2.57	3.12	1.67
654	988	2,668.98	2.27	3.14	1.56
846	970	2,924.46	3.01	3.27	1.84
931	950	3,116.38	3.28	3.53	1.97
1078	951	3,359.84	3.28	3.53	1.97
1991	1435	3,405.26	2.37	3.06	1.27
2136	987	3,717.46	3.77	3.76	2.43
2372	1065	2,858.46	2.68	3.33	1.56
2456	875	3,351.30	3.83	3.76	2.36
3775	1001	2,940.88	2.94	3.51	1.86
Total	10,258	31,009.67	3.02	3.47	1.38

Table D.2 Over-heading distance (from driver accepted to passenger pick-up) summary statistics according to GPS measured data

Driver ID	Number of Rides	Total Distance	Mean	Std. Dev.	Median
		(miles)			
357	1,232	894.62	0,73	0.94	0.40
654	1,174	1,071.53	0.91	1,06	0.63
846	1,085	1,218.67	1.12	1.26	0.72
931	1,098	840.74	0.77	1.12	0.38
1078	1,220	1,365.34	1.12	1.23	0.72
1991	1,636	1,519.32	0.93	1.16	0.51
2136	1,150	1,241.36	1.08	1.25	0.67
2372	1,296	1,186.15	0.92	0.98	0.59
2456	1,069	1,257.81	1.18	1.17	0.89
3775	1,129	715.58	0.63	0.79	0,36
Total	12,089	11,311.11	0,94	1.11	0.57

The average over-heading distance for less than 1-hour empty durations between rides was measured as 0,88 miles, while for the before the first ride for each shift was determined as 1.24 miles. However, for this part, over-heading distances were calculated by taking an average of all measured distance before each trip.

Table D.3 Empty Trip distance (Worst-case scenario) summary statistics according to drivers for less than 1-hour empty duration

Driver ID	Empty Trips	UVMT	Additional UVMT	Empty Distance	Average distance per trip
		(miles)			
357	1,036	2,666.63	3,119.37	5,786.00	5.58
654	988	2,668.98	2,241.99	4,910.97	4.97
846	970	2,924.46	2,498.02	5,422.48	5.59
931	950	3,116.38	2,322.19	5,438.57	5.72
1078	951	3,359.84	3,066.20	6,426.04	6.76
1991	1435	3,405.26	3,696.94	7,102.20	4.95
2136	987	3,717.46	3,093.77	6,811.23	6.90
2372	1065	2,858.46	2,213.92	5,072.38	4.76
2456	875	3,351.30	1,963.98	5,315.28	6.07
3775	1001	2,940.88	2,548.51	5,489.39	5.48
Total	10,258	31,009.67	26,764.90	57,774.57	5.63

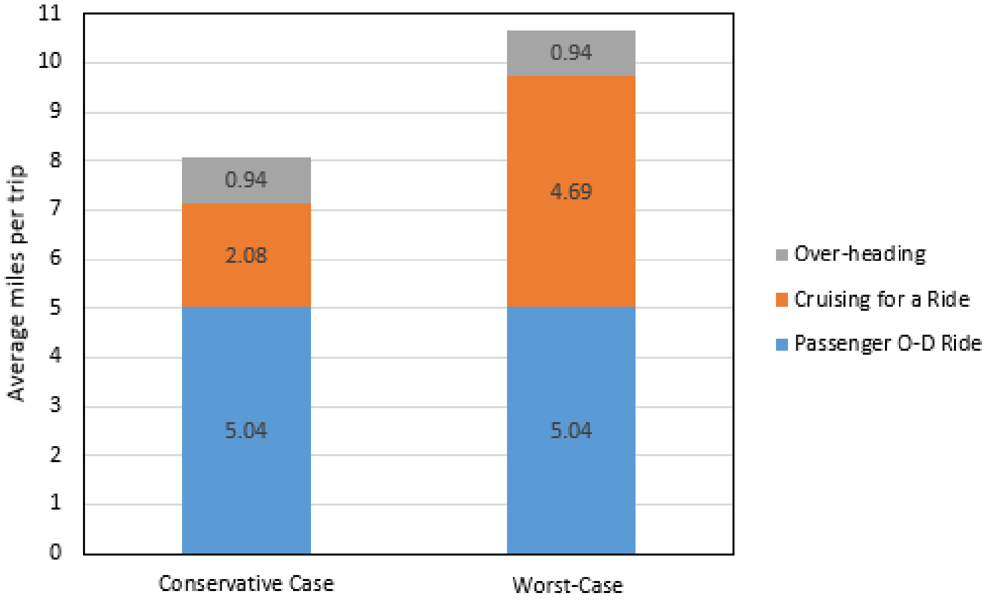

Figure D.1 Average miles per trip for both scenarios

Figure D.1 shows the average mile per trip segments according to scenarios, including passenger ride, over-heading, and cruising for a ride. However, the commuting part was not included in the calculations. It is assumed that GPS based measured over-heading distance that is travelled distance from driver accepted to ride request to passenger pick-up location is inside the determined empty trip. In other words, distance from (D) to (2-E) was assumed that inside the empty trip direction from previous ride end (1-B) to next ride origin (2-E), (see in Figure 3.6).

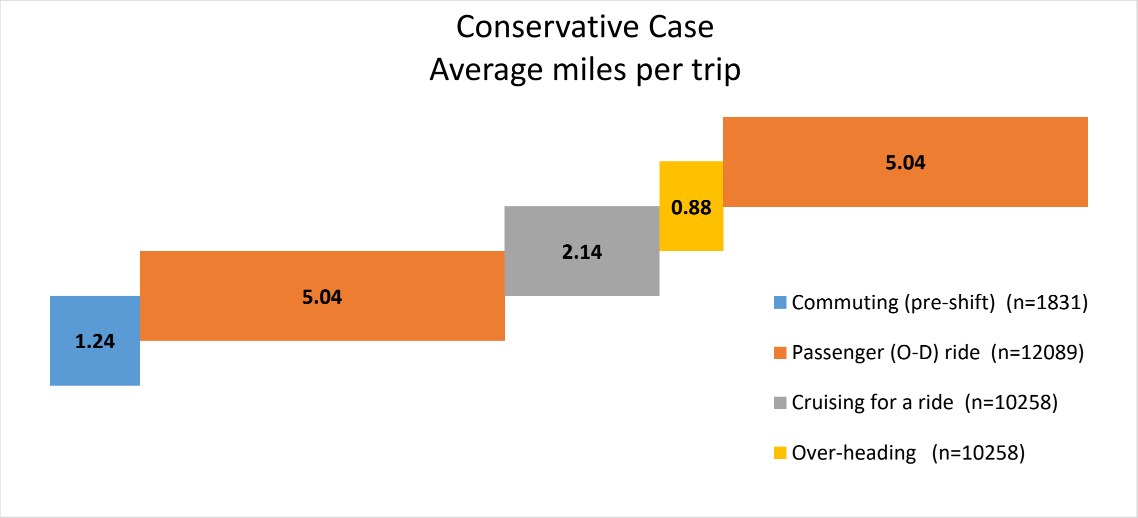

Figure D.2 Average miles per trip for the conservative case

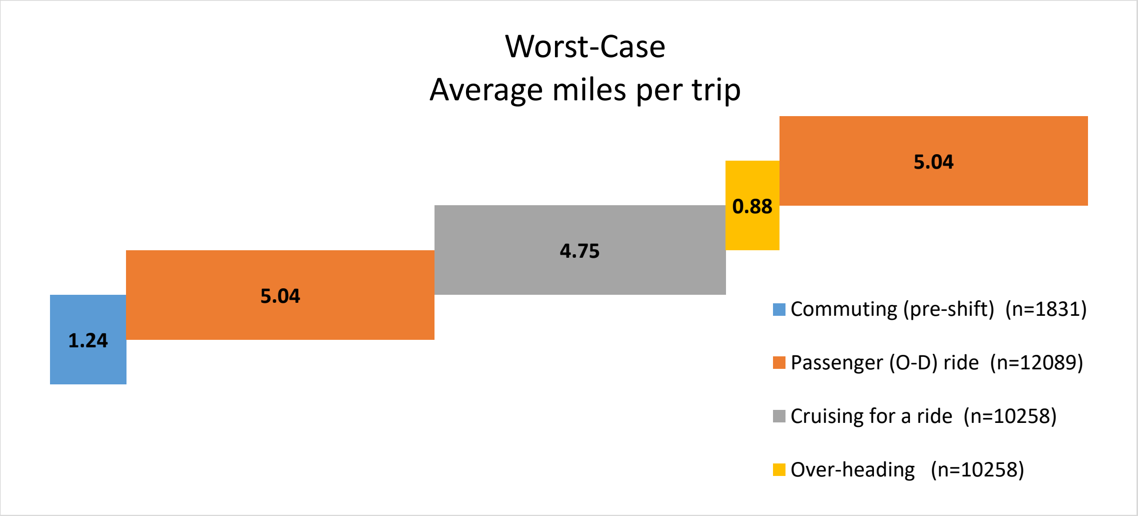

Figure D.3 Average miles per trip for the worst-case scenario

The results that are indicated in Figure D.2 and D.3 was measured by considering commuting segments of before each shift. As previously mentioned, RideAustin dataset provides the GPS measured distance from drivers accepted the ride request location to passenger pick-up locations. Therefore, this data can give approximate distance for pre-shift commuting by segregating corresponding data. However, it should be noted that the estimated average miles per trip of each segment were not considered in calculating the efficiency of ride-hailing services. The main reason for that, number of trips per driver and working period and days are varying between driver. For these reasons, efficiency results were determined based on the total values of ten drivers, rather than average values.

APPENDIX E: DATA ANALYSIS RESULT SUMMARY FOR LESS THAN 2 HOURS EMPTY DURATION

Table E.2 Drivers shift details for less than 2 hours empty duration

Driver ID	Rides	Empty Trips	Shifts	Working Days	Shift per Working Day	Rides per Shift
357	1,232	1,114	118	78	1.51	10.44
654	1,174	1,050	124	78	1.59	9.47
846	1,085	1,014	71	62	1.15	15.28
931	1,098	1,001	97	74	1.31	11.32
1078	1,220	1,028	192	88	2.18	6.35
1991	1,636	1,490	146	87	1.68	11.21
2136	1,150	1,052	98	86	1.14	11.73
2372	1,296	1,131	165	85	1.94	7.85
2456	1,069	922	147	78	1.88	7.27
3775	1,129	1,042	87	56	1.55	12.98
Total	12,089	10,844	1,245	772	1.61	9.71

Table E.2 Waiting or cruising for a ride time (time from rides ends to dispatch) summary statistics for less than 2 hours empty duration

Driver ID	Number of Empty Rides	No Cruising for a ride	Total	Mean	Std. Dev.	Median
			(hh:mm:ss)			
357	1114	11	305:39:00	00:16:28	00:20:32	00:08:51
654	1050	24	248:08:11	00:14:11	00:20:07	00:00:03
846	1014	17	210:59:55	00:12:29	00:16:50	00:05:49
931	1001	18	238:59:17	00:14:19	00:18:35	00:07:45
1078	1028	23	284:15:11	00:16:35	00:21:42	00:08:30
1991	1490	37	307:46:18	00:12:24	00:17:43	00:05:46
2136	1052	34	275:19:47	00:15:42	00:19:51	00:08:28
2372	1131	35	245:35:34	00:13:02	00:19:35	00:05:13
2456	922	19	216:48:40	00:14:07	00:19:11	00:07:20
3775	1042	9	241:22:15	00:13:54	00:16:51	00:08:13
Total	10844	227	2574:54:08	00:14:15	00:19:10	00:07:10

Table E.3 Calculation of additional Unoccupied Vehicle Miles Travelled (UVMT) for less than 2 hours empty duration

Driver ID	Total Ride Distance (miles)	Total Ride Duration (sec)	Mile per second	Empty Trip Duration - UVHT (sec)	Additional UVMT (miles)
357	5,410.07	824,359	0.0066	793,080	5,204.80
654	5,433.70	890,987	0.0061	617,906	3,768.31
846	5,658.74	859,011	0.0066	540,297	3,559.21
931	5,812.53	758,518	0.0077	512,841	3,929.90
1078	7,577.35	960,233	0.0079	699,871	5,522.79
1991	7,375.86	1,148,800	0.0064	817,695	5,250.00
2136	6,247.80	790,308	0.0079	652,152	5,155.60
2372	6,318.90	999,045	0.0063	622,655	3,938.26
2456	5,906.79	841,435	0.0070	476,484	3,344.87
3775	5,231.39	800,407	0.0065	560,783	3,665.23
Total	60,973.12	8,873,103	0.0069	6,293,764	43,248.73

Table E.4 Times Ride-hailing efficiency summary for less than 2 hours empty duration

Driver ID	PHT	UVHT (Google Maps)	Empty Duration	Maximum VHT	Minimum VHT	PHT/ Max VHT	PHT/ Min VHT
	(hh:mm:ss)					(%)	
357	228:59:19	148:02:17	393:12:13	622:11:32	377:01:36	36.80	60.74
654	247:29:47	141:01:22	340:35:40	588:05:27	388:31:09	42.08	63.70
846	238:36:51	139:35:39	313:35:29	552:12:20	378:12:30	43.21	63.09
931	210:41:58	143:17:55	314:25:47	525:07:45	353:59:53	40.12	59.52
1078	266:43:53	152:24:07	372:20:54	639:04:47	419:08:00	41.74	63.64
1991	319:06:40	177:28:08	438:05:42	757:12:22	496:34:48	42.14	64.26
2136	219:31:48	168:35:25	379:20:54	598:52:42	388:07:13	36.66	56.56
2372	277:30:45	142:45:40	347:53:35	625:24:20	420:16:25	44.37	66.03
2456	233:43:55	144:33:44	303:45:48	537:29:43	378:17:39	43.49	61.79
3775	222:20:07	140:36:44	319:51:02	542:11:09	362:56:51	41.01	61.26
Total	2464:45:03	1498:21:01	3523:07:04	5987:52:07	3963:06:04	41.16	62.19

Table E.5 Efficiency of ride-hailing service in terms of vehicle miles travelled (VMT) for less than 2 hours empty duration

Driver ID	**PMT**	**UVMT**	**Additional UVMT**	**Minimum VMT**	**Maximum VMT**	**PMT/ Max VMT**	**PMT/ Min VMT**
	(miles)					**(%)**	
357	5,410.07	3,166.70	5,204.80	8,576.77	13,781.56	39.26	63.08
654	5,433.70	3,190.54	3,768.31	8,624.24	12,392.55	43.85	63.00
846	5,658.74	3,320.46	3,559.21	8,979.19	12,538.40	45.13	63.02
931	5,812.53	3,448.26	3,929.90	9,260.79	13,190.70	44.07	62.76
1078	7,577.35	4,177.42	5,522.79	11,754.77	17,277.56	43.86	64.46
1991	7,375.86	3,796.48	5,250.00	11,172.34	16,422.34	44.91	66.02
2136	6,247.80	4,212.47	5,155.60	10,460.27	15,615.87	40.01	59.73
2372	6,318.90	3,338.17	3,938.26	9,657.08	13,595.33	46.48	65.43
2456	5,906.79	3,725.77	3,344.87	9,632.55	12,977.42	45.52	61.32
3775	5,231.39	3,154.11	3,665.23	8,385.49	12,050.72	43.41	62.39
Total	60,973.12	35,530.37	43,248.73	96,503.49	139,842.46	43.60	63.18

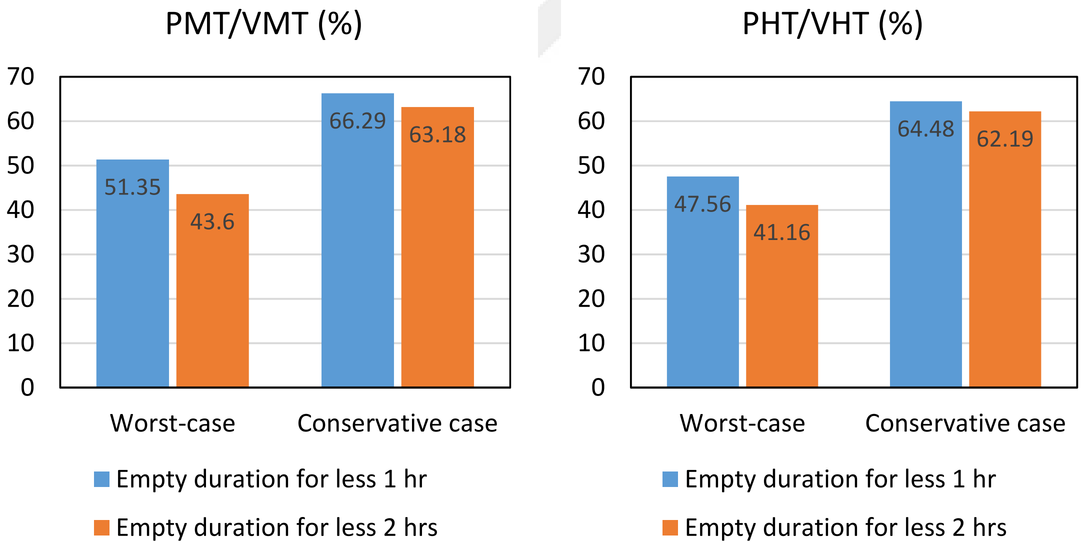

Figure E.1 Ride-hailing efficiency rates for less than 1 hour and 2 hours